JELLE DE VRIES

Behavioral Operations in Logistics

BEHAVIORAL OPERATIONS IN LOGISTICS

Behavioral Operations in Logistics

Gedragskundige invloeden in de logistiek

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When I was young, my biggest dream was to work in a warehouse. No, I am not being honest here, I had just never been to one. My actual dream was to become a bus driver, controlling more horsepower than a forklift commonly offers, and some interaction with passengers as added bonus. How could a warehouse job, characterized by an apparent repetitiveness of work and limited room for human interaction, be motivating and inspiring at all? In the end my career as a bus driver never ignited, but somehow the role of people in determining performance and efficiency became the focus of my daily life for the past years as a PhD Candidate. Pursuing a PhD was never something I imagined or planned, and it could not have been imagined without the indispensable guidance, assistance, and support of several persons who contributed greatly to the process leading to the completion of this dissertation.

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Contents

Chapter 1

Introduction

1.1 Behavioral Operations

Operations Management (OM) is a broad field of study, covering not only the "design and management of the transformation processes in manufacturing and service organizations that create value for society" (Chopra et al., 2004, p. 12), but also "the search for rigorous laws governing the behaviors of physical systems and organizations" (Chopra et al., 2004, p. 8). Encompassing such a broad range of topics, OM frequently overlaps with other academic streams, such as quality management, operations research (OR), finance, and marketing, and employs methods from these streams. However, as could be expected based on the "rigorous laws" mentioned in the description of the OM field, the methods employed in OM research are generally heavily oriented towards normative mathematical models instead of empirically testing causal relations (Chopra et al., 2004; Wacker, 1998). This approach has proven to be highly valuable for the advancement of the field of OM in the past and will continue to be critical for the field in the future. However, at the same time it is vital that OM allows itself to depart from the assumption that all agents participating in operating systems or processes – ranging from decision-making managers to workers – are fully rational or at least act that way (Bendoly et al., 2006; Gino and Pisano, 2008).

After Simon (1991, 1955) and Tversky and Kahneman (1974) emphasized the limited capabilities and biases of humans in learning, thinking and acting, their theories found their way into a variety of scientific disciplines. For instance, fields such as economics, marketing and finance have successfully incorporated behavioral aspects. Through the introduction of theories such as prospect theory (Kahneman and Tversky, 1979) and the consideration of emotions these fields have departed from complete rationality and can all boast thriving behavioral research streams. The field of OM has been relatively late in following this trend and the field of behavioral operations has only recently been able to achieve the status of an established area within the discipline of operations management (Bendoly et al., 2010; Croson et al., 2013). However, the field has witnessed rapid growth during the last decade, increasing from 52 behavioral operations papers published between 1985 and June 2005 (Bendoly et al. 2006), to over 100 behavioral operations papers published between 2006 and 2011 (Croson et al. 2013). Even though this growth has brought a variety of high quality studies, new topics, and methodological approaches, studies focused on human judgement and decision-making are currently dominating the research in the field (Croson et al., 2013). At the same time, there still exist scarcely researched areas that deserve to be explored, such as the role of differences between individuals in influencing operational outcomes (Moritz et al., 2013).

As with every field of study, a necessary condition for achieving the 'established' status has been the provision of a clear definition of the area of behavioral operations and its boundaries. According to Croson et al. (2013), behavioral operations can be defined as "the study of potentially non-hyper-rational actors in operational contexts" (p. 1). Gino and

Pisano (2008) define the field as "the study of human behavior and cognition and their impacts on operating systems and processes" (p. 679). Even though these two definitions differ slightly in their wording, in essence they overlap: research in behavioral operations covers topics that entail behavioral as well as operational elements. The field of behavioral operations focuses on operations in the sense that the main goal is understanding and improving operating systems and processes, and is employing the potential effects of human behavior in achieving this goal (Bendoly et al., 2006). However, as Loch and Wu (2005) point out, some specification of the 'effects of human behavior' in behavioral operations research is appropriate to illustrate the broadness of the field in itself. Even though early definitions might have suggested that these effects are almost exclusively biases in the decision-making of individuals, it is important to realize that factors such as leadership, motivation, and social interactions on the level of groups can also play a role.

Furthermore, we propose that the impact on operational processes and outcomes is not sufficiently specific in describing the actual scope of the field. It is important to realize that the 'behavior' in behavioral operations does not only potentially refer to the influence of behavioral factors on traditional operational outcomes such as productivity, quality, or profit, but that less easily quantifiable outcomes such as safety and employee well-being can be considered as well.

To apply more structure to this dissertation and to be able to clearly point out its contributions, we make a distinction between the internal and external influences on human behavior in operational processes and the different types of outcomes of these processes. We elaborate more upon this distinction in the following sections.

The field of behavioral operations management has expanded in terms of methods as well. In addition to more traditional simulation studies and mathematical models, we now also observe an increased use of empirical methods such as field case studies, surveys, and (controlled) experiments in the field of behavioral operations management. (Bendoly, 2013, 2011; Bendoly et al., 2010). However, rather surprisingly, behavioral insights and research methods are still rarely applied to the field of supply chain management and especially to lower-level operational tasks in contexts such as production and (intra)logistics (Tokar, 2010). The studies conducted by Doerr et al. (2004) and Schultz et al. (2003) are rare examples of the successful application of behavioral experiments in the context of repetitive operational labor, by focusing on the impact of different types of work policies on the performance of individual workers. Through this approach they demonstrate the potential insights that can be obtained using a behavioral approach that does not aim to explain human decisions and judgment, but investigates the role of the individual behavior of the actors who most directly influence operational outcomes: the workers. This dissertation aims to further explore this approach gap by studying the influence of several behavioral aspects and individual differences in the context of logistics.

1.2 Behavioral Operations in logistics

The Council of Supply Chain Professionals defines logistics management as the “part of supply chain management that plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services and related information between the point of origin and the point of consumption in order to meet customers' requirements” (CSCMP, 2015). Almost every aspect of this definition involves the work of people, and deviations from their assumed rational behavior can substantially influence (intra)logistical processes and their outcomes. In this dissertation, we focus on some of the most important internal and external factors behind such potential deviations from rational behavior of individuals, and their influence on the more traditional operational outcomes productivity and quality as well as on outcomes such as safety leadership and occupational safety.

Outcome measures

In this dissertation we distinguish two different types of outcomes measures: the ‘traditional’ operational outcomes of productivity and safety, and occupational safety.

Productivity and quality. Productivity, quality, and the relationship between these aspects have traditionally been the most commonly studied outcomes in OM research, and have frequently been used as synonyms for performance. This is not surprising, since these constructs can be measured relatively easily and are closely related to financial performance, the most important target for most companies. Because of the central role of these constructs, quality and productivity serve as outcome measures in most of the chapters in this dissertation.

Occupational safety. Considering occupational safety as outcome measure is less popular, which is partly reflected by the rare presence of safety-related aspects in mission statements of companies (Amato and Amato, 2002). Safety is commonly merely regarded as a necessary factor of which a certain minimum level should be present to enable a focus on other company goals. Not considering safety as a proper outcome or goal impedes the establishment of relationships between company policies and safety, and potentially leads to occupational accidents that could have been prevented. In chapters 5 and 6 of this dissertation we demonstrate how safety (behavior) can be used as outcome measure in two different contexts.

Behavioral factors

We treat two types of behavioral factors in this dissertation: internal behavioral factors, which refer to characteristics of individual persons, and external behavioral processes, which refer to characteristics of the environment of these individual persons.

Internal behavioral factors: Regulatory Focus. The regulatory focus of individuals determines how they interpret the world around them and what actions and decisions they take to reach specific goals (Higgins, 1998, 1997, 1987). According to regulatory focus theory, two different regulatory foci exist: a promotion focus, which is related to an aim for positive outcomes and rewards, and a prevention focus, related to security and the avoidance of negative outcomes. The regulatory focus of individuals describes how individuals aim to accomplish desired goals and reach desired end states. Because of this, regulatory focus is regarded as an important determinant of behavior (Lanaj et al., 2012) and is implicitly also closely related to observable outcomes. This makes the construct of regulatory focus particularly suitable to employ in explaining operational outcomes, which is demonstrated by the prominent role of regulatory focus in several chapters of this dissertation.

Internal behavioral factors: Personality. Another common method to describe individuals and differences between them is by evaluating their personality traits. The Big Five model of personality (Digman, 1990) employs five dimensions to describe human personality: conscientiousness, openness, agreeableness, extraversion, and neuroticism. Conscientiousness in particular, but also several of the other four personality traits, have frequently been linked to various aspects of job performance (Barrick and Mount, 1991; Barrick et al., 2001). This, and the fact that the Big Five model is the most popular method used to distinguish individuals led us to employ the Big Five model of personality traits as predictor of operational outcomes in several two chapters of this dissertation.

External behavioral factors: SSTL. Several studies have emphasized the role of leadership, and particularly safety-specific transformational leadership (SSTL) in fostering occupational safety (Barling et al., 2002; De Koster et al., 2011). Through this type of leadership, leaders influence, inspire, stimulate, individually consider, and reward their employees with respect to safe working practices and outcomes. However, not much is known about the determinants of SSTL, and about its relationship with traditional operational outcomes such as productivity and quality. Chapter 5 of this dissertation addresses exactly these issues.

External behavioral factors: Incentive systems. The use of incentive systems has been proven to be one of the most effective methods for companies to influence the motivation of their employees (Guzzo et al., 1985). Various different types of incentive systems exist to achieve this goal. Examples include individual-based incentives, team-based incentives and competition-based incentives. The effectiveness of incentive systems is partly dependent on factors such as the degree of independence/interdependence of the task (Wageman, 1995; Zingheim and Schuster, 2000), but differences between individuals can also play a role (Wageman and Baker, 1997). The proven effectiveness as well as the unpredictability of the influence of incentive systems on operational outcomes makes it particularly interesting to study incentive systems through a combination of a behavioral perspective and an application in an operational setting.

1.3 Contributions and outline of the dissertation

In this thesis, we demonstrate the influence of these behavioral factors through different mechanisms and in various logistical contexts. All chapters (besides the introduction and conclusion) are stand-alone empirical research articles that can be read in isolation. Since chapters 2, 3, and 4 all treat the topic of order picking, some overlap on this topic exists between these chapters. The contributions of the individual chapters are summarized below.

Chapter 2. Aligning Order Picking Methods, Incentive Systems, and Regulatory Focus to Increase Performance

In chapter 2 we focus on order picking, one of the most costly tasks in a typical warehouse environment. A unique controlled field experiment investigates order picking performance in terms of productivity and quality to answer the following research question: what is the best combination of order picking method, incentive system, and regulatory focus to achieve high order picking performance? We examine three manual picker-to-parts order picking methods (parallel, zone, and dynamic zone picking) under two different incentive systems (competition-based versus cooperation-based) for pickers with different regulatory foci (prevention-focus versus promotion-focus). The study was carried out in a warehouse erected especially for the purposes of order picking research to optimally combine the scientific rigor of a controlled experiment with the practical generalizability of a field study.

Chapter 3. Pick One for the Team: The Effect of Individual and Team Incentives on Parallel and Zone Order Picking Performance

Chapter 3 extends chapter 2 by executing an order picking experiment in a laboratory environment instead of a real warehouse environment, and by investigating different incentive systems. The experiment examines order picking performance (in terms of productivity and quality) of parallel picking and zone picking, and aims to find out which incentive system works better in combination with each picking method. However, rather than the cooperative and competitive incentive systems that were studied in chapter 2, this study investigates the effect of individual and team incentive systems.

Chapter 4. Exploring the role of picker personality in predicting picking performance with pick by voice, pick to light, and RF-terminal picking.

Chapter 4 extends the previous two chapters by incorporating another important aspect of order picking: the order picking tool. The task of order picking can be executed using various different tools, and we propose that not all order pickers are able to work equally well with all tools. Therefore, this chapter revolves around the following research question: What is the role of individual differences in picking performance with various picking tools (pick by voice, RF-terminal picking, and pick to light) and methods (parallel, zone, and dynamic zone picking)? A field experiment with professional pickers and students as participants is employed to investigate the influence of individual differences, especially Big Five personality traits, on picking performance in terms of productivity and quality.

Chapter 5. Safety Does Not Happen by Accident: Antecedents to a Safer Warehouse

On a daily basis, thousands of employees suffer from severe occupational accidents worldwide - often with severe consequences. A large portion of these accidents take place in warehouses. Prior research has demonstrated the critical role of leadership and especially safety-specific transformational leadership (SSTL) in reducing warehouse accidents. Chapter 5 answers several important remaining research questions: what effects does SSTL have on outcomes other than safety (such as productivity and quality), and what determines whether leaders display SSTL behaviors? These questions are answered using survey data from warehouse managers and employees.

Chapter 6. Which Drivers Should Transport Your Cargo? Empirical Evidence from Long-Haul Transport

Chapter 6 focuses on the influence of behavioral aspects on an essential process in the supply chain outside of the warehouse, namely road transport. Truck drivers are encounter many unsafe situations on the road and face continuous pressure to combine driving safely with meeting productivity targets. Not all drivers respond equally well to these demands. Using a combination of GPS data, survey data, and data obtained from the enterprise resource planning system, this study addresses the following research question: what is the role of individual driver characteristics (safety consciousness and personality in particular) in predicting risky driving behavior and driving productivity?

Chapter 7. Summary and Conclusions

This chapter summarizes the previous studies by discussing the main findings, scientific relevance, managerial relevance, and potential avenues for future research.

Overall Contribution

Overall, we demonstrate the influence of internal as well as external factors on two different types of organizational outcomes: safety and productivity. This is summarized in Table 1. We believe the distinction between internal and external behavioral factors provides the field of Behavioral Operations Management with a structure that can be employed in the positioning of future studies. Furthermore, through focusing on safety and productivity as organizational outcomes we aim to highlight not only that safety should be an important objective of any organization, but also that safety and productivity are not necessarily at odds with each other.

Table 1: Summary of overall contributions: variables impacting safety and productivity

	Safety	**Productivity**
Internal behavioral factors	Big-five Prevention focus	Big-five Regulatory focus
External behavioral factors	Leadership (SSTL)	Incentive systems

1.4 Contributions to this thesis

This section summarizes which organizations and individuals have been involved in the research contributing to this thesis.

Data collection

- Data for chapter 5 were provided by 87 warehouses, and partly overlaps with De Koster et al. (2011) for 55 warehouses. Dutch industry association of material handling suppliers BMWT assisted in recruiting warehouses to participate, as well as several student assistants.
- Data for chapters 2 and 4 were gathered using a field experiment in a realistic warehouse environment. The materials to create this warehouse environment, materials and space were provided by the Material Handling Forum (MHF), BMWT, and Zadkine. Student assistants Tom Dellebeke and Ramon De Koster assisted in the execution of the experiment.
- Data for chapter 3 were gathered using a laboratory experiment in the Erasmus Behavioral Lab with the assistance of student assistants Jan Rohof and Yuvensianti Therecia.
- Data for chapter 6 were gathered by Debjit Roy and Rochak Gupta at RCI Logistics in India.

Research

Most of the research presented in this thesis was executed independently by the author. The author has studied the relevant literature, performed all analyses, and wrote the chapters that make up this thesis. However, the following co-authors have contributed substantially to the quality of the research in the following chapters:

- Chapters 1, 2, 3, 4, 5, and 7: René de Koster and Daan Stam were involved in defining the research questions, developing the conceptual frameworks, providing continuous feedback on the analyses, and improving the writing of the chapters.
- Chapter 6: René de Koster, Serge Rijsdijk, and Debjit Roy were involved in the development of this project and improved the chapter by providing continuous feedback on the analyses and writing.

Publishing Status

Chapter 4 has been accepted for publication:

> De Vries, J., R. De Koster, D. Stam. 2015. 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 (ahead of print).

Chapters 2, 5, and 6 have been submitted to scientific journals and are currently at various stages of the review process.

Chapter 2

Aligning Order Picking Methods, Incentive Systems, and Regulatory Focus to Increase Performance

2.1 Introduction

Companies are under constant pressure to investigate how warehousing costs can be reduced to remain competitive. At the same time the market share of e-commerce is growing, which often implies that warehouses have to meet increasing customer demands by offering speedier delivery and tighter and more flexible delivery windows (Frazelle, 2002). This puts pressure on virtually all warehouse processes. One of these processes, order picking, *the retrieval of a number of products from their storage locations in the warehouse to satisfy orders of specific customers*, is an essential activity in the supply chain and accounts for up to 50% of the operating costs of a typical warehouse (Tompkins 2010). Due to this relatively large share of costs, studying how order picking productivity can be improved could lead to substantial cost-savings. Most of the current academic literature on order picking productivity focuses on optimizing or improving technical or system-related aspects of particular picking methods such as routing (De Koster et al., 2007; Hwang et al., 2004; Petersen, 2004), storage assignment (Jarvis and McDowell, 1991), warehouse layout (Hsieh and Tsai, 2006), and zoning (Jane and Laih, 2005; Le-Duc and De Koster, 2005). As an addition to this line of research, we argue that *human factors* strongly affect performance in tasks such as order picking and consequently focus on behavioral factors that influence performance in order picking. We test this using a field experiment in a real warehouse environment.

More specifically, in the current study we investigate to what extent the incentive system, order picking method, and regulatory focus of pickers influences picking performance. Compensation and incentive systems are among the most effective strategies to influence employee behavior, motivation, and performance (Guzzo et al., 1985). However, not all incentive systems lead to optimal performance under all conditions, and people respond differently to specific incentive systems (Wageman and Baker, 1997). Specifically, it appears that competitive incentive systems (such as employee of the month schemes) are especially effective under circumstances in which individuals work independently (Dobbins et al., 1991). In contrast, incentives directed at cooperation are especially effective under circumstances that emphasize task interdependency (Wageman, 1995; Zingheim and Schuster, 2000). The most common order picking methods (parallel picking, zone picking, and dynamic zone picking) differ in the extent to which they are considered independent or dependent, with parallel picking being considered independent, zone picking dependent, and dynamic zone picking falling in between these two. This suggests that competitive incentives may be most suited for parallel picking, cooperative incentive most for zone picking, and both incentives could be effective in a dynamic zone context. Moreover, we argue that these fit effects of incentive and picking method may differ dependent on the individual worker's attitudes and inclinations. Specifically, regulatory focus theory (Higgins, 1998), a major theory of individual differences, distinguishes between individuals that are oriented on achieving their personal ideals and ambitions using eager strategies (promotion focus) and individuals that are oriented on fulfilling their duties and obligations using vigilant strategies (prevention focus). Recent research shows that promotion-focused individuals are more sensitive to individual incentive schemes, while prevention-focused individuals are more sensitive to group incentive schemes (Beersma et al., 2013). As a consequence we argue that a promotion focus may enhance the effects of competitive incentives, while prevention focus may enhance the effects of cooperative incentives.

Our study makes both theoretical and practical contributions. Although prior research has established that an alignment between incentive systems and task is important for optimal performance (e.g. Jenkins Jr et al., 1998), the exact nature of this alignment for order picking is unclear. We offer a new model of the alignment of incentive systems and order picking tasks by focusing on cooperative and competitive incentive systems and their effectiveness under parallel, zone, and dynamic zone picking methods. This extends the more global models of incentives systems by adapting them to the domain of order picking. Moreover, we also integrate individual differences in this equation. Specifically, we identify regulatory focus as a crucial individual difference and test its moderating effects on the influence of incentive systems. Together, this leads to a much-extended model of incentive systems that is specific to the domain of order picking. We believe this model has the potential to explain variance in order picking unaccounted for by current models.

Our contributions also extend theory. For instance, much of the research on incentive systems in Operations Management (OM) is theoretical in nature and our research extends this by detailing empirical evidence of the effects of incentive systems in actual order picking and how incentive systems depend on picking method and individual differences. From a managerial point of view, identifying under which circumstances different types of people reach their optimal performance levels could be particularly beneficial not only because companies could be aided in training and selecting the right employees for the job, but also in determining which incentive system should be used in combination with which order picking method and type of employee.

In the remainder of this paper, we first review the literature on order picking, incentive systems, and regulatory focus. Next, we introduce our hypotheses, describe our methodology and our performance measures. We then present our analyses and results. We conclude by discussing the practical impact of correctly aligning the picking method, the incentive system, and the regulatory focus of the individual pickers, and how our findings can be implemented in practice.

2.2 Theory

Order picking

As a pivotal step in a product's route to a customer, order picking can be regarded as a crucial warehouse operation. The full order picking process involves all steps from clustering and scheduling customer orders to disposing the picked articles. In many of these steps, a certain degree of automation is possible, but most warehouses employ humans as order pickers (De Koster, 2007). In this paper, we focus on the most common picking system, low-level picker-to-parts picking with multiple picks per route, in which the order picker has to walk along the aisles to fulfill the order by picking all specified items. This picking system contrasts with parts-to-picker systems that use of automated storage and retrieval systems (AS/RS) or carousels (De Koster et al., 2007).

Various technological picking tools can be used in low-level picker-to-parts systems. For example, pickers can be aided by hand-held scanners, voice-terminals, or pick-to-light systems. Here, we only focus on the traditional order picking using a paper picking list. There are also various picking methods. In this study we include three of the most common methods: parallel picking, sequential zone (pick and pass) picking, and dynamic zone (bucket brigade) picking. In *parallel picking*, pickers work on their own order from the beginning to the end. This means that the pickers work almost independently of each other. In *sequential zone picking*, the warehouse or aisle is divided into separate zones. Each picker is responsible for one zone, and an order is passed on to the picker in the next zone when the order is completed in the zone. If an order does not contain any lines to be picked in a particular zone, the order is passed on to the next zone immediately. If the picker in the next zone is still busy with a previous order, the current order can be placed in a buffer. In other words in zone picking, pickers depend on each other to perform well. In *dynamic zone picking* the volume determines the end of the zone, so there is no fixed zone limit. Rather than waiting at the zone limit until the upstream picker is finished with his/her zone, a picker will travel towards the upstream picker and the order will be transferred at the meeting point. Theoretically, this eliminates waiting time or large buffers between zones (Tompkins et al., 2010). Therefore, dynamic zone incorporates both independent as well as dependent features and can be placed somewhere between parallel picking and zone picking in terms of dependency

Prior studies focus on various aspects of the order picking process to increase efficiency. Examples include the layout of the picking area (Caron et al., 2000), the product storage strategy (Jarvis and McDowell, 1991), sequencing and routing (Caron et al., 1998; Goetschalckx and Donald Ratliff, 1988; Ratliff and Rosenthal, 1983), and batching (Elsayed, 1981; Rosenwein, 1996). This research has also looked at picking policies (parallel, zone, and dynamic zone) and concluded that the effectiveness of order picking policy depends heavily on the properties of the particular warehouse (e.g., warehouse shape, type of storage rack, product type and size, and required throughput) (Hsieh and Tsai, 2006; Hwang and Cho, 2006; Petersen, 2004; Yu, 2008). Based on the results of these studies, warehouse managers have been able to make better decisions about which order picking system to implement to improve performance and decrease operating costs. However, there is still room for improvement. For instance, although humans make the picks in these systems, the influence of the picker has generally been ignored. Work elements of an order picker in a low-level picker-to-parts system include tasks such as traveling to pick locations (about 50% of a picker's time), searching for pick locations (about 20% of a picker's time), and picking the items (about 15% of a picker's time) (Tompkins et al., 2010). Setting up the order that has to be picked or starting to pick again after short interruptions is also time consuming (Schultz et al., 2003). We argue that the effort, motivation and actions of individual pickers are also important factors that influence the performance of manual order picking systems. Consequently, these behavioral aspects need to be included in research on order picking performance.

In the current study, we focus on this influence of the order picker by keeping factors such as the picking area, product layout, and sequencing constant, and by investigating behavioral factors that influence a picker's performance in terms of productivity. More specifically we emphasize two elements that may facilitate optimizing performance given a certain picking policy: Incentive systems and picker regulatory focus. Next, we discuss the literature on incentive systems and hypothesize which incentive system is most effective under which picking policy. Then we move to picker characteristics in terms of regulatory focus and discuss how this affects the influence of the incentive system.

Incentive systems

Awarding financial incentives to reward performance is a common method to align the efforts of employees with the objectives of the company and to improve productivity (Gomez-Meja and Balkin, 1989). Previous studies have emphasized that financial incentives are among the most important drivers of employee performance (Jenkins and Gupta, 1981; Jenkins Jr et al., 1998; Locke et al., 1981, 1980). Although some studies argue that offering external rewards such as money may undermine intrinsic motivation (Eisenberger and Cameron, 1996; Kohn, 1993a, 1993b), a meta-analysis of 39 studies by Jenkins Jr et al. (1998) showed a substantial corrected correlation of .34 between financial incentives and performance quantity.

Organizations frequently have to choose between implementing an incentive system that is completely based on individual performance, or rather adopt a cooperation-based reward scheme in which the group performance determines at least part of the individual pay. Besides choosing for either individual or team focused incentive systems, companies can also choose to highlight the importance of either competition or cooperation among employees (Tjosvold, 1986). In a competitive marketplace, rewards are often also based on relative performance (Nalebuff and Stiglitz, 1983). Examples of such 'contest' reward schemes are bonuses for the employee-of the month or compensation plans based on a ranking of the employees in terms of sales or productivity performance. A possible reason to implement such reward schemes can be that social comparison processes (Festinger, 1954) among team members in a competitive incentive scheme could stimulate them to reach higher performance at their job. Furthermore, it is generally cheaper to monitor relative performance levels than absolute performance levels, in particular if only few prizes for the top performers are being awarded (O'Keeffe et al., 1984).

The exact circumstances under which cooperative incentives or competitive incentives are unclear, but task interdependence has been identified as one of the most critical factors influencing the effectiveness of rewarding teams (Rosenbaum et al., 1980; Wageman and Baker, 1997). Task interdependence refers to the degree of interaction and cooperation between team members that is required to complete a specific task (Sundstrom et al., 1990). The literature on the topic has consistently demonstrated that matching tasks and rewards lead to higher performance (for an overview, see Wageman and Turner; 2001). This implies that it is more effective to use competitive incentives for independent tasks, and cooperative incentives for interdependent tasks.

If these findings are translated to the context of order picking, we can hypothesize which incentive system leads to better performance when used in combination with a particular order picking method. For example, a parallel picking system entails a relatively low degree of interdependence. Pickers work individually on a task, and are not required to communicate and coordinate work with other pickers. They know that they are responsible for their own performance, and are likely most motivated if the incentive system fits these circumstances, i.e. under a competitive incentive system. An increase in motivation at work has commonly been linked to a variety of positive outcomes, such as a higher productivity (Kanfer et al., 2008). Therefore, a competitive incentive system is expected to perform especially well in the context of parallel picking, which is stated in the first hypothesis.

Hypothesis 1: Competition-based incentives outperform cooperation-based incentives in terms of productivity in parallel picking.

In a zone picking system, pickers work in a team. Each picker only finishes part of an order and as a consequence the throughput time of an order is dependent on the performance of each individual picker. Moreover, in a situation with limited buffers, the maximum work speed of a worker in a later zone is serially dependent on the on the speed of the workers in the earlier zones (Schultz et al., 1999). Thus, zone picking is associated with a high degree of task interdependency. Since high levels of task interdependency are a facilitator of the motivating effects of a group incentive system, pickers will probably be more motivated at work if the incentive system is group oriented to a certain extent as well. Since motivation should influence productivity, it follows that the productivity performance of pickers working with a zone picking method are higher under an incentive system that focuses more on cooperation.

Hypothesis 2: Cooperation-based incentives outperform competition-based incentives in terms of productivity in zone picking.

Dynamic zone picking is -to some degree- a combination of parallel picking (since the individual performance of pickers determines where they hand over products to other pickers) and zone picking (with flexible zone boundaries). In other words dynamic zone picking includes both task elements that are independent in nature as well as task elements that are interdependent in nature. However, since we do not exactly know how to characterize dynamic zone picking in terms of interdependence (closer to parallel picking, or rather closer to zone picking) we cannot make any prediction about the effects of competitive and cooperative incentives in dynamic zone picking.

Regulatory focus

The effects of incentive systems described above may differ for different workers. To gain more insight into this issue we employ regulatory focus theory. This theory, first coined by Higgins (1997, 1998), is based in psychology and is well-suited to be employed in investigating any type of motivation that drives people to achieve certain goals (Higgins, 1998). It can be described as a mindset that influences how people think and act. Regulatory focus theory distinguishes between two self-regulatory strategies that influence behavior. A promotion focus emphasizes accomplishing desired, attractive, and positive goals and aims at achievement, growth, and advancement. A prevention focus emphasizes fulfilling duties, responsibilities, and obligations, and includes an element of fear of failing (Higgins, 1998). Also, prevention-focused people are often more risk-averse than promotion-focused people (Halvorson and Higgins, 2013). In contrast with personality theories and measures such as the Big Five (Digman, 1990), regulatory focus theory has been more directly linked to behavior. Some studies even suggest that the relationship between personality traits and individual behavior is actually mediated by the regulatory focus of individuals (Lanaj et al., 2012). Since incentive systems are aimed at influencing the motivation and behavior of workers, regulatory focus is a relevant construct to investigate in the context of this study. Although promotion and prevention focus are two theoretically distinct constructs, several studies suggest that an emphasis of one type of regulatory focus mitigates the effects of the other type (Shah and Higgins, 2001; Zhou and Pham, 2004). For example, a person with a dominant promotion focus is unlikely to be partly guided by a prevention focus at the same time. Because of this, we follow Lockwood et al. (2002) in expecting that the dominant regulatory focus of order pickers influences performance, rather than the individual effects of both regulatory foci.

In the context of order picking performance, we expect that the influence of each of the two regulatory foci partly depends on the type of performance. Prevention-focused people tend to follow rules and regulations conscientiously and to avoid errors (Higgins, 1997; Wallace et al., 2009), which suggests that they could make fewer picking errors. A promotion focus, on the other hand, has been linked to production performance (Wallace et al., 2009, 2008) and to sensitivity to the presence or absence of rewards (Kark and Van Dijk, 2007). However, these results are not generally applicable, and are subject to a very influential factor: the fit between people's regulatory focus and the goal that they have to pursue (Higgins, 2000). For example, Shah et al. (1998) showed that more promotion-focused people performed substantially better in an anagram task if the briefing and task itself emphasized obtaining gains rather than avoiding losses. The results were reversed for prevention-focused people. This finding suggests that people are more sensitive to information congruent with their dominant regulatory focus. Regulatory fit has also been linked to a higher task enjoyment (Freitas and Higgins, 2002).

Similarly, whether a task is executed individually or in a team also has a different effect on people with a different regulatory focus. Lee et al. (2000) showed that promotion-focused people rated individual events as more important than prevention-focused individuals, whereas the situation is exactly the opposite for team events. The same holds for the rewards structure. In an experiment, Beersma et al. (2013) showed that more prevention-focused teams were more engaged and performed better with a cooperation-based incentive system than with an individual-based incentive system while the reverse was true for promotion-focused teams.

Based on these findings we argue that the fit of the picking method and the incentive system is especially beneficial if it also fits the regulatory focus of the picker. For example, the hypothesized better performance of parallel picking with a competition-based incentive system is expected to be especially pronounced for more promotion-focused pickers, who generally place more emphasis on their own achievements and potential positive outcomes and thus are especially motivated by a competitively oriented task and incentive system. This is reflected in hypothesis 3:

Hypothesis 3: Competition-based incentives outperform cooperation-based incentives in terms of productivity for dominantly promotion-focused pickers in parallel picking.

Zone picking and a cooperation-based incentive system, on the other hand, is a good combination especially for more prevention-focused pickers, who place more emphasis on team performance as we expect them to be especially motivated by a group-oriented task and incentive scheme. This combination is likely not so suitable for more promotion-focused pickers, who emphasize individual performance. Thus the difference between a cooperation-based incentive system and a competition-based incentive system in zone picking is therefore most likely larger for prevention-focused pickers, while the incentive system is not expected to make a substantial difference for more promotion-focused pickers in zone picking. This leads to hypotheses 4a, and 4b.

Hypothesis 4: Cooperation-based incentives outperform competition-based incentives in terms of productivity for dominantly prevention-focused pickers in zone picking.

Dynamic zone picking is a mix of an independent and dependent picking method. Theoretically it should be more productive than regular zone picking, assuming that the work rate of the pickers is stationary and not affected by the requirement to coordinate where an order should be passed on. However, Doerr et al. (2004) found that a dynamic zone policy at an experimental production line did not outperform a fixed zone policy, partly as a consequence of higher worker heterogeneity and worker variability. This result suggests that individual differences between workers determine how motivated they are for a task that is characterized by a mix of independent and interdependent work.

We argued earlier that both competition-based incentive schemes and cooperation-based incentive schemes could be motivating in dynamic zone picking. Here we extend this reasoning by posing that the dominant regulatory focus of the pickers may determine which aspect of the task (teamwork or individual work) is the most salient and hence which incentive scheme would be more motivating with a dynamic zone picking method. Lee et al. (2000) used an experimental approach to find that when a prevention focus is salient in independent tasks, individuals rate events with interdependent (team) outcomes as more important than independent (individual) outcomes. Exactly the opposite pattern emerged with a salient promotion focus. It is likely that people are more motivated to work hard to achieve an outcome that they perceive as being important. Therefore, we also expect that for pickers with a dominant prevention focus the interdependent aspects of dynamic zone picking would be highly salient and consequently that a cooperative incentive scheme would be more motivating than a competitive incentive scheme. In reverse, we expect that for pickers with a dominant promotion focus the independent aspects of dynamic zone picking would be highly salient and consequently that an individual incentive scheme would be more motivating than a group incentive scheme. This leads to hypothesis 5a and 5b.

Hypothesis 5a: Competition-based incentives outperform cooperation-based incentives in terms of productivity for dominantly promotion-focused pickers in dynamic zone picking.

Hypothesis 5b: Cooperation-based incentives outperform competition-based incentives in terms of productivity for dominantly prevention-focused pickers in dynamic zone picking.

2.3 Methodology

Participants

The hypotheses were tested using data obtained from an experiment with 143 participants arranged into 48 three-person teams. Because of missing data for one or more of the relevant testing variables, data of 14 individuals could not be used in the subsequent analyses. This also implied the removal of two teams. The resulting sample size consisted of 129 participants arranged in 46 teams. Additionally, for each experimental session there was also a quality inspector, whose sole task was to check the work of the three pickers. The role of quality inspector was normally performed by people who subscribed to participate to the experiment, but a confederate of the experimenter worked as quality inspector in 8 teams because only three people had subscribed to the particular timeslots. Whether a participant or a confederate served as quality inspector had no noticeable impact on the performance outcomes of the team. In two teams, a confederate of the experimenter worked as order picker to substitute for last minute cancellations of participants. These teams both worked in a parallel picking setup, to minimize the interaction between the confederate and the two other pickers. The confederate was experienced at the task and was instructed to work at an average pace, and the performance of these confederates and their teams was close to the average performance in the condition they were assigned to. The results of these pickers were not taken into consideration. Of the 129 participants, 28 (20%) were university students studying business, 39 (27%) were professional warehouse employees, and 75 (53%) were logistics students at a vocational college, training to become future warehouse employees.

The university students were recruited through notifications on the university's intranet, and through emails to all students in various courses. Regardless of performance and incentive condition, each student received €20 in exchange for their participation. The professional order pickers were recruited through a recruitment agency and through contacting various companies active in the Dutch warehousing sector. Ten companies provided at least one participating team of order pickers. The professional pickers also received €20 for their participation, regardless of how they performed. Of the 129 participants 77.5% were male, 49.2% were aged between 16 and 20, 26.6% aged between 21 and 25, and 24.2% aged between 26 and 48. Of the 129 pickers, 62.8% of the participants did not have any order picking experience, whereas 16.3% had worked as order pickers for at least one year. Most participants (70.5%) were Dutch native speakers and completed the questionnaires in Dutch. Of the remaining participants, 11.6% filled out English questionnaires and 17.8% completed Polish questionnaires. The Polish respondents were all warehouse professionals.

Procedure

The experiment took place in an experimental warehouse setup (Figure 1). This warehouse was especially erected with the support of several material handling suppliers, supplying racks, picking carts, labels, dummy products, and a Warehouse Management System (WMS). This approach was chosen because order picking is a task that is difficult to replicate realistically (in terms of travel distances, layout, picking heights, product sizes and weights, professional full-size equipment) in a regular laboratory environment, and laboratory experiments can therefore suffer from generalization issues: results obtained in the lab could be unrepresentative for what happens in practice. A field experiment combines the manipulation of independent variables and random assignment to conditions in a completely controlled setting with an environment and task that are highly similar to order picking in practice. This approach should provide findings that are not only obtained through a methodologically rigorous approach, but also are highly generalizable to practice.

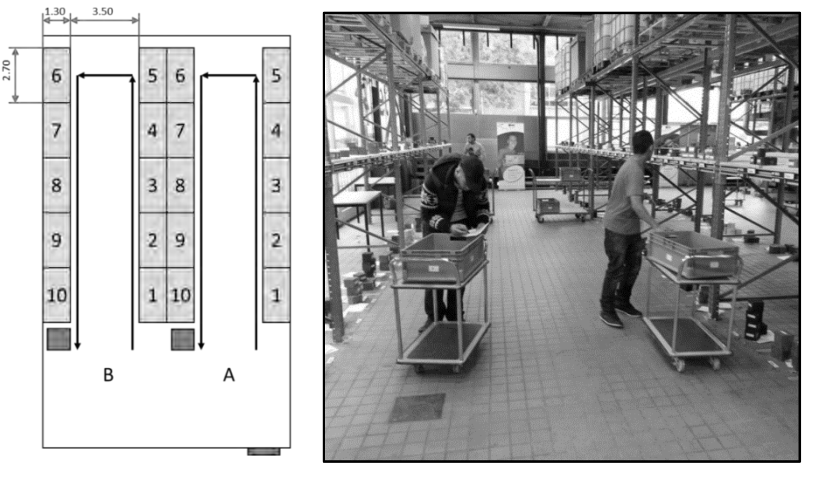

Figure 1: Experimental warehouse layout (measures are in meters)

The 1000 colored and labeled wooden dummy products ranging in volume from 0.2 to 2 liters and in weight from 50g to 500g were placed at two sides of two (identical) warehouse aisles. The two identical aisles allowed us to execute two simultaneous experimental sessions. The aisles were divided in 10 sections, each containing 5 locations with 2 levels. The locations were logically numbered. For example location A05.3.1 meant that the product was stored in aisle A, in section 5, at location 3 on the lower level. Participants used picking carts to transport the crates (one crate per order). After filling out a pre-questionnaire containing questions on demographic information and regulatory focus, the pickers did a practice round of an order picking task in which they had to pick as many orders with as few errors as possible in 10 minutes, while using a particular method, and subject to a particular incentive structure. On average, the orders contained 8.38 order lines ($\sigma = 2.35$, log-normally distributed) and each order line prescribed the picking of one or two units ($\mu = 1.5$) of a particular product. The pickers had to pick the quantity of the correct product, and mark the picking list once a line was picked. Each team worked with the same set of orders. The experimenter used a stopwatch to record start and finish times of each order. When an order was completed, the quality inspector checked whether the pickers had made any mistakes (wrong quantity, wrong product, etc.). The pickers were told that their performance was being tightly monitored by an additional check by one of the experimenters. After a short break, the participants helped to replace the dummy products in their original location. Subsequently, the ‘real’ run of the same task started, also lasting 10 minutes. In zone picking, the participants were assigned to a zone-based on their speed in the practice run: the fastest picker in the first zone, the second-fastest picker in the second zone, and the slowest picker in the last zone. This ensured that all pickers could reach their full performance potential. Furthermore, even though in zone picking pickers work in separate zones, helping each other was still possible to a certain extent, for example by neatly sorting the products in the crate, or by pointing out where a colleague had to make the next pick. Participants completed a post-questionnaire before the end of the experiment. This questionnaire contained a measurement of job-satisfaction which was not used in the remainder of the study. The experiment ended after the dummy products had been replaced and after a short debriefing. The total duration was approximately one hour per group. The experiment was part of an experimental session lasting two hours in total, but all data used for this paper were obtained in the first hour.

Manipulations & Measures

The experiment used a 3×2 between-subjects design, with picking method and incentive condition as independent factors. Picker teams were randomly assigned to the conditions.

Picking methods: We used three paper picking methods: 47 participants used parallel picking, 47 used zone picking, and 48 employed dynamic zone picking. The zones used for zone picking are shown in Figure 1, with section 1-3 as part of zone one, section 4-7 as part of zone two and section 8-10 as part of zone three. The zones were delimited by a table that served as a buffer. The second zone consisted of four sections, whereas the first and third zone only consisted of three sections. This setup was chosen based on several pilot sessions to balance the workload of all pickers by compensating for the potential shortcut in the U-shape that the second picker could take if no products had to be picked in section 5 or 6. We controlled for this in the analyses.

Motivational incentives: Sixty-one participants (distributed across the three methods), had to complete as many orders as possible without making errors working together (cooperation-based incentive system). They were told that if *the performance of their entire team as a whole* was the best among all participating teams they would each get a bonus. By working together all team members could win a prize, thus creating the willingness to cooperate to reach this incentive. The other 68 participants had to individually complete as many orders as possible without making mistakes (competition-based incentive system). They were told that *the individual performance of only the best team member* would be compared to that of other best team members and if it was amongst the best four of all participating individuals, he or she would get a personal bonus. Thus, only one team member could win a prize by performing better than the other team members, creating competition. In both conditions, the winners (all four members of the best performing team, and the four best performing individual pickers) received a €100 voucher for a large electronics & media retailer. The groups participants were randomly assigned to a picking method and incentive condition.

Productivity was measured by counting the amount of *correctly* completed order lines per individual during the real picking run of 10 minutes, ensuring that the pickers had already become familiar with the method in the practice round.

We also employed *Quality* as outcome variable, because factors that increase productivity might have a negative impact on quality at the same time. However, no significant effects of the independent variables on quality were identified and quality was therefore not included in the remainder of the analyses. Quality was measured by the percentage of orders per individual that contained errors during the real picking round. This measure was preferred to the percentage of individual order lines that contained errors to prevent an inflation of the error percentage (because of stacking error on error in a single order). The quality inspector of each team checked whether each order contained the right types and numbers of products. We told the quality inspectors that their accuracy would be compared to other quality inspectors in the experiment by randomly checking 25% of the orders, and that the best quality inspector could win a €100 voucher. The checks revealed that the quality inspectors hardly made mistakes.

Promotion focus (α=.798) and *prevention focus* (α=.849) were measured using the average scores on Wallace and Chen's (2006) Regulatory Focus at Work Scale in the first questionnaire that the participants completed. This scale has proven its validity and internal consistency in various work contexts (Wallace et al., 2009). A principal component analysis (PCA) with oblique (oblimin) rotation was conducted on the 12 items of the scale. The Kaiser-Meyer-Olkin measure showed an excellent fit (KMO = .872), and the KMO values for all individual items proved to be high (>.77) as well. Bartlett's test of sphericity (χ^2 (66) = 677.4, p < .001) showed that the correlation matrix of the items is no identity matrix, which makes the items suitable for use in PCA. The scree plot confirmed that the twelve items are well represented by two components, jointly explaining 55.6% of the variance. Table 2 shows the structure and pattern matrix of the rotated factors. The clustering of the items revealed that factor 1 represents prevention focus, and factor 2 represents promotion focus. The prevention focus score of each participant was subtracted from his/her promotion focus score and the resulting difference score was standardized to arrive at a measure of the participant's *dominant regulatory focus*. The actual average (unstandardized) values of the dominant regulatory focus (promotion minus prevention) were −5.28 for participants with a dominant prevention focus and −.21 for participants with a dominant promotion focus. This dominant regulatory focus is employed because, as explained in section 2.3, even though a single individual can theoretically to a certain extent be promotion and prevention focused at the same time, we believe that behavior is primarily guided by the focus that is most dominantly present. Subsequently, following Lockwood et al., (2002) a median split (the median was −.33) was performed to end up with a binary dominant regulatory focus measure. This facilitates a direct comparison between participants with a relatively dominant promotion focus and those with a relatively dominant prevention focus.

In addition to *participant background*, *age* (in years), *education* (highest level completed), and *experience* with order picking (in months) of the participants were used as control variables. These controls differ significantly across background, but since we also control for participant background this does not influence the testing of our hypotheses. We also introduced a dummy variable indicating whether a participant was the second or third order picker in the zone or dynamic zone picking method. This was done to control for the different picking situations of the second and third picker, who are, to a certain extent, dependent on the first picker in these methods.

The dominant regulatory focus questionnaire was translated to Dutch and Polish to ensure that non-native English speaking participants could understand all the questions. Ninety-one participants filled out the Dutch version of the questionnaires, 23 completed the Polish version, and 15 filled out the English version. The reliability of the various scales proved to be >.70 for all languages. We used two-way analyses of covariance (ANCOVA) to examine whether differences in dominant regulatory focus could be identified across the three languages, after controlling for participant background. We found no effect of language on dominant regulatory focus ($F(2, 124) = 2.09$, $p = .13$). Therefore, the three different languages of the questionnaires will not be considered as a factor in the subsequent analyses.

We also measured job satisfaction of the participants using an adapted version of Hackman and Oldham's Job Diagnostic Survey (1974) but since we did not have any hypotheses regarding this dependent variable and also did not identify any noteworthy findings, we do not elaborate on this construct in the remainder of the manuscript. However, the appendix of this chapter includes some of the analyses involving job satisfaction.

Table 2: Regulatory focus at work scale (Wallace and Chen 2006) + pattern and structure matrix factor analysis (Oblimin rotation)

	Component 1 (prevention)		Component 2 (promotion)	
Items	Structure	Pattern	Structure	Pattern
4.1 Following rules and regulations at work	0.66	**0.56**	0.49	0.21
4.2 Completing work tasks correctly	0.82	**0.83**	0.4	-0.02
4.3 Doing my duty at work	0.82	**0.83**	0.41	-0.01
4.4 My work responsibilities	0.78	**0.84**	0.32	-0.1
4.5 Fulfilling my work obligations	0.84	**0.83**	0.44	0.02
4.6 On the details of my work	0.62	**0.54**	0.42	0.15
4.7 Accomplishing a lot at work	0.48	0.16	0.72	**0.65**
4.8 Getting my work done no matter what	0.21	-0.17	0.68	**0.76**
4.9 Getting a lot of work finished in a short amount of time	0.38	-0.05	0.83	**0.85**
4.10 Work activities that allow me to get ahead at work	0.45	0.16	0.65	**0.57**
4.11 My work accomplishments	0.46	0.22	0.59	**0.48**
4.12 How many job tasks I can complete	0.45	0.09	0.77	**0.72**
Eigenvalues	5.26		1.41	
% of variance	43.8		11.8	
α	0.8		0.85	

Note: Pattern loadings over .40 appear in bold

2.4 Analyses, results, and effect sizes

Backgrounds

First, we checked for differences in performance and dominant regulatory focus between the participants from different backgrounds (university, professional picker or vocational education), after controlling for the method and incentive condition (Table 3). It might seem surprising that university students scored relatively high compared to professional pickers. However, the professional pickers were not necessarily familiar with the order picking method or tool employed in the experiment. Furthermore, general cognitive ability has proven to be an important predictor of performance in different types of jobs (Ree et al., 1994), which could partly explain the relatively high performance of students. To account for these differences, we included participant background as a fixed control factor (using dummy variables) in the relevant subsequent analyses.

Table 3: Means and Standard Deviations per Participant Background

	University		Professional		Vocational	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Lines*	53.21	2.6	46.34	2.1	40.38	1.48
Dom. RF	-0.36	0.55	-0.66	0.53	-0.41	0.52
Experience	0.17	0.83	29.54	49.22	3.49	7.72
Education	2.39	1.47	2.89	0.94	2.33	0.6
Age	19.39	2.23	32.68	8.72	19.87	3.39

*means controlled for picking method, incentive condition, picking experience, education, and age.

Lines = error-free order lines picked, errors = % orders with error(s), Dom. RF = Dominant regulatory focus (higher = more promotion focus, lower = more prevention focus).

Descriptives and group-level properties

Subsequently, we examined the descriptive statistics of the key variables. Table 4 shows significant correlations of education with dominant regulatory focus and age, and of age with the percentage of orders with errors and with order picking experience. These correlations suggest that it is important to control for age, education and order picking experience in the analyses.

Table 4: Means, standard deviations, and correlations between key variables

	Variable	Mean	Std. dev.	1	2	3	4
1	Error-free order lines picked	44.58	15.77	-			
2	Dom. RF	-0.47	0.54	0.01	-		
3	Age (years)	23.48	7.94	0.1	-0.1	-	
4	Education (levels 1-5)	2.51	0.94	-0.07	**-.22***	**.18***	-
5	Experience (months)	10.37	29.38	-0.01	-0.17	**.61****	0.06

* $p < .05$, ** $p < .01$

Dom. RF = Dominant regulatory focus (higher = more promotion focus, lower = more prevention focus).

Note: $N = 129$. Pairwise deletion of missing values employed, resulting in a lower N for some correlations.

We then investigated how much of the variance in the outcome variables could be explained by the team-level (the 46 three-person picking teams) and how much is attributable to the aggregation of the data of individual team members. This analysis was performed according to the steps explained by Bliese (2009), using the multilevel package within R 3.0.1 (R Core Team, 2013).

First, we calculated the intraclass correlation coefficients ICC(1) and ICC(2) (Bliese, 2009) of the dependent variables and performed Random Group Resampling (RGR) with 960 pseudo-groups (Bliese and Halverson, 2002) to examine whether controlling for the fact that the participants were nested in 3-person groups was required (Table 5). Group membership explained a part of the variance for the number of correct order lines picked. Based on these results, we tested for multilevel effects in the subsequent analyses.

Table 5: Group-level properties

	ICC(1)	ICC(2)	RGR z-value	RGR p-value (one tailed)
1. Error-free order lines picked	0.32	0.57	-1.83	0.034

Productivity

As initial step, we compared the fit of a model without a random intercept with one that contained a random (group dependent) intercept in predicting the number of correct order lines picked. These models were fit using the 'lme' and the 'gls' functions in the 'nlme' package (Pinheiro et al., 2013) in R 3.0.1 (R Core Team, 2013). The categorical variables (participant background, picking method, incentive condition, and dominant regulatory focus) were treated as N-1 dummy codes in the model matrix to be included in the model. Based on a-2 log likelihood test, the random intercept model appeared to fit significantly better than the model without the random intercept ($\Delta = 9.86$, $p < .01$). Subsequently, we created a linear mixed-effects model with a random intercept and participant background, age, education, and order picking experience as control variables. Furthermore, we controlled for the position of the pickers in a zone or dynamic zone picking method.

Three-way interaction between picking method, incentive system, and regulatory focus: In the model, displayed in Table 6, the picking method, incentive system, dominant regulatory focus, as well as the two- and three-way interaction are included as predictors. The highest order interaction effect is included immediately because it could have a substantial influence on the interpretation of the main effects (Moore et al., 2008). We employed the marginal and conditional R^2 as described by Nakagawa and Schielzeth (2013) to estimate the model fit. For this model, the fixed effects (average effects around which individual observations vary randomly) explain 50% of the variance in productivity (marginal R^2), and the entire model (individual + group effects) explains 71% of the variance (conditional R^2). The three-way interaction between picking method, incentive proved significant ($F(2,72) = 3.46$, $p = .037$). Inspection of the three-way interaction plots (Figure 2) and a comparison of the marginal (controlled) means reveal that in parallel picking, competition-based incentives significantly outperformed cooperation-based incentives for promotion-focused pickers, supporting hypothesis 3. No difference between the incentive systems was found for prevention-focused pickers in parallel picking, in line with hypothesis. In zone picking, cooperation-based incentives significantly outperformed competition-based incentives not only for prevention-focused pickers, but also for promotion-focused pickers. The first is in line with hypothesis 4, and the second result suggests that regulatory focus does not matter in this case. In dynamic zone picking, no differences between the incentive systems were identified for both promotion-focused and prevention-focused pickers. Therefore, hypotheses 5a and 5b were not supported.

Table 6: Linear mixed-effects model with random (group) intercept. Dependent variable: order lines picked. Type III sum of squares.

Fixed effects	F-value	Df numerator	Df denominator
Intercept	**55.16****	1	72
Age	0.92	1	72
Participant background	**4.15***	2	38
Picking experience	0.08	1	72
Education	0.24	1	72
Picking position 2	**15.13****	1	72
Picking position 3	**28.01****	1	72
Picking method	1.96	2	38
Incentive condition	0.73	1	38
Method × condition	0.21	2	38
Dom. RF	**8.16****	1	72
Method x Dom. RF	**5.07****	2	72
Condition × RF dominance	**9.42****	1	72
Meth. × cond. × RF dom.	**3.46***	2	72

Marginal R^2	0.5
Conditional R^2	0.72
# of groups	45
# of individual observations	129

Dom. RF = Dominant regulatory focus (higher = more promotion focus, lower = more prevention focus)

** p < .01, * p < .05

Two-way interaction between picking method and incentive condition: To draw conclusions about the first two hypotheses we first inspect Figure 2. This figure suggests that in general cooperative incentives deliver better productivity results in zone picking than competitive incentives, supporting hypothesis 2. In parallel picking, the subject of hypothesis 1, the result is more nuanced. It is necessary to consider the regulatory focus of participants in stating which incentive system delivers the highest productivity in parallel picking. Hypothesis 1 can therefore not be confirmed. The similar performance under competition-based and cooperation-based incentive conditions of dynamic zone picking suggest that this method can indeed be considered as a combination of the other two methods. Table 7 provides an overall overview of which of the hypotheses were supported by the analyses.

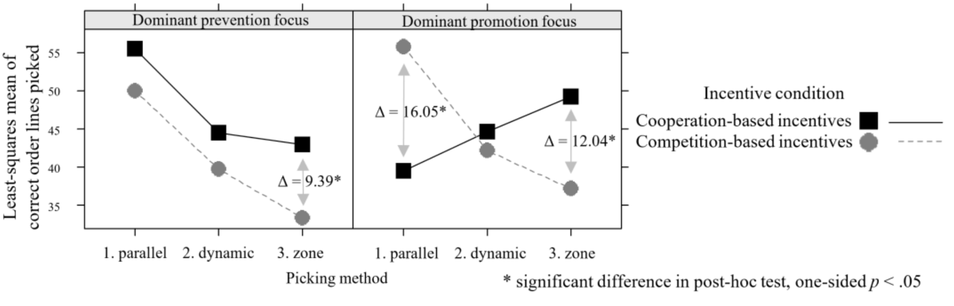

Figure 2: Three-way interaction between picking method, incentive condition and dominant regulatory focus on productivity

Table 7: Overview of hypothesis testing results

Hypo	Supported?	Hypo	Supported?
1	Partly		
2	✓		
3	✓		
4	✓		
5a	×	5b	×

Effect sizes

Not only the statistical analyses and absolute numbers, but especially the effect sizes of the behavioral factors illustrate the impact that a change of incentive system or type of employee can have on productivity in practice. Table 8 shows performance improvements in a given picking method if the incentive system is changed or if pickers with a different dominant regulatory focus are deployed. Not all differences between combinations of picking method, incentive system, and regulatory focus are significant, but this table serves as illustration of the effect sizes. The combination of incentive system and possibly regulatory focus with the lowest performance in the particular picking method is used as a baseline and is assigned a score of 100 (representing a different productivity level in both picking methods). The scores of the other combinations reveal their performance compared to the baseline.

Table 8: Comparison of effect sizes (Baseline = 100)

	Parallel picking productivity	Zone picking productivity
Cooperation-based incentive, prom. dominance	**100**	147.5
Cooperation-based incentive, prev. dominance	140	123.9
Competition-based incentive, prom. dominance	140	111.5
Competition-based incentive, prev. dominance	130.4	**100**

Table 8 shows that in parallel picking, switching from the worst scenario to the best scenario in terms of incentive system and regulatory focus could result in productivity benefits of 40%. In zone picking, this potential benefit adds up to 47.5%.

2.5 Conclusion and discussion

The importance of the order picking process in the supply chain emphasizes the need for research that optimizes this process. Whereas most of the literature on this topic focuses on aspects such as optimizing product-to-location assignment, picker zoning, order batching, and picker routing, this study contributes to the literature by demonstrating the influence of behavioral factors on order picking performance in a controlled field-experiment.

Implications for practice

In this study, we found that by optimally combining a given order picking method with either a cooperation-based or a competition-based incentive system can yield great benefits in terms of productivity. Additional benefits can be reaped by assigning employees with a particular regulatory focus to a picking method and incentive system that best fits their regulatory focus.

For most companies, the potential positive effects of implementing an incentive system in general are probably no surprise. However, the best type of incentive and the magnitude of the effects of the choice between incentive systems might be not so well known. It should be emphasized that this study only compares a cooperation-based and a competition-based incentive system. Most likely, the benefits for companies that currently do not have an incentive system are even larger. According to a meta-analysis by Condly et al. (2003), incentive systems deliver overall average performance gains of 22% compared to a situation without incentive systems. Implementing the findings of this study in practice requires incentives that can be realistically made part of the company's reward structure. For individual incentives, an example of this is employing piece-rate pay in addition to a base wage. In our situation, this could be paying employees an additional amount per completed pick or order (a statistic registered by many warehouses already). Something similar could be implemented at the team level, in which case the additional amount is based on the team performance. It should be noted that also non-monetary incentives, such as small prizes or privileges, can be effective (Jeffrey and Shaffer, 2007).

Regulatory focus is relatively easy to measure with a questionnaire. As many warehouses use multiple picking methods in different parts of the facility (De Koster et al., 2007), companies might try to assign people with a particular regulatory focus to the right type of picking process, or even use regulatory focus as one of the selection criteria in the hiring process. As we have found, in a parallel picking method competitive incentives are more productive than cooperative incentives for people with a dominant promotion, whereas in zone picking cooperative incentives are more productive overall. To make use of these findings, companies can re-assign employees with a particular dispositional regulatory focus to tasks that are better aligned with their regulatory focus. However, depending on the methods used, this option might not be present. Alternatively, the regulatory focus of a person can be influenced by situational cues. Companies can evoke a promotion or prevention focus by framing the tasks in particular ways. For example, to evoke a promotion focus, companies will have to frame the task in terms of potential gains, whereas a prevention focus can be evoked by framing the task in terms of potential losses (Crowe and Higgins, 1997).

Implications for theory

Through this experiment, we found that aligning the right incentive system with the right picking method can lead to increased productivity.

Productivity: Multilevel analyses revealed that team effects account for a substantial part of the variance (21%) in productivity performance in order picking. This is an important primary insight, especially when considering that we studied ad-hoc teams rather than teams that have been working together for a longer time. Regarding the alignment of picking method and incentive systems, the findings show that in parallel picking, competition-based incentives outperform cooperation-based incentives for promotion-focused pickers (supporting hypothesis 3 and partly supporting hypothesis 1). In zone picking the order is reversed for promotion- as well as prevention-focused pickers (supporting hypotheses 2 and 4). In dynamic zone picking the difference between the two incentive systems was negligible. The overall results endorse the theory that individualized incentive schemes are more effective when the task is more independent (such as parallel order picking), whereas cooperation-based incentive schemes are more effective if the task requires interdependent operation.

Furthermore, the results that show the influence of the combination of regulatory focus, method, and incentive system on productivity are novel. In parallel picking, competition-based incentives deliver significantly higher productivity than cooperation-based incentives for promotion-focused individuals (supporting hypothesis 3). In zone picking, cooperation-based incentives delivered a higher productivity for both prevention- and promotion-focused individuals (supporting hypothesis 4). In dynamic zone picking, no differences between the two incentive systems were identified for participants with a prevention-focus as well as for participants with a promotion focus (not supporting hypotheses 5a and 5b). The performance of the pickers in the current study suggests that dynamic zone picking fits between parallel and zone picking based on the degree of interdependence between workers, but this deserves to be researched more extensively.

The performance improvement realized by optimally utilizing these findings illustrates the impact that regulatory focus and incentive systems can have in addition to the choice of a picking method. This is most likely not only relevant to the context of order picking, but could be applicable to all types of repetitive labor. Investigating this in a different context while possibly taking other behavioral factors into account could be interesting in this respect.

Strengths and Limitations

The use of a controlled field experiment in a setting that represents the situation in practice is an evident strength of this study. This provides the required academic rigor, and enables a smooth translation of the findings to practice at the same time. However, like all academic research, this study is subject to several limitations. First of all, a larger sample size would have been preferable to ensure that the effects that occur are statistically noticeable. Still, 129 participants is an acceptable number in the 3x2 between-subjects design that was employed. Second, the academic students that participated in the experiment are probably less representative of order pickers. However, we tried to mitigate this problem by including professional order pickers (approximately one third of the total sample), and logistics students training to become future warehouse employees (half of the sample). This should ensure sufficient external validity to generalize the results to workers in practice. Third, the relatively short time scale of the experiment could endanger the generalizability. The performance could be influenced by the fact that the experiment only required 20 minutes of order picking, of which only 10 minutes were used for data collection. Doing the job for a complete day, week, or even year, could potentially alter the results. For example, pickers might be satisfied with a certain picking method in combination with a specific incentive system for 20 minutes, but could become dissatisfied after a longer period. Still, the relatively short time scale is inherent to our experimental setup.

Conclusion

Aligning regulatory focus, incentive systems, and order picking methods helps to close the gap that exists between operations management theories and their applicability to practical settings. The use of a controlled field-experiment which included both professional order pickers and students as participants has enabled us to obtain results that are generalizable to practice without compromising on scholarly rigor.

Appendix

Besides studying the potential influence of behavioral factors on typical operational outcomes such as productivity and quality, it is also possible to consider behavioral outcome measures. In the study presented in this chapter we also considered job satisfaction as outcome variable. These results are not presented in the chapter itself to maintain focus on the key constructs. To avoid that these analyses and results will not be available at all, they are presented in this appendix.

Job satisfaction (α=.805) was measured using the general job satisfaction scale of Hackman and Oldham's Job Diagnostic Survey (1974). This scale consists of five statements that describe the views of employees on their own job, and their expectations of the opinion of their coworkers on the job. To make the scale more applicable to the context of the experiment, the word 'job' was replaced by the word 'task'. The items, shown in Table 9, were rated using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Items two and five were reversely coded. The aggregate of the five items was standardized before being used in the subsequent analyses. Table 10 displays the standardized means and standard deviations of job satisfaction per participant background, revealing similar job satisfaction scores for all groups of participants.

Table 9: Adapted job diagnostic survey (Hackman and Oldham, 1974)

3.1 Generally speaking, I am very satisfied with this task.
3.2 I frequently think of quitting this task.
3.3 I am generally satisfied with the kind of work I do in this task.
3.4 Most people working on this task are very satisfied with the task.
3.5 People working on this task often think of quitting.

Table 10: Job Satisfaction Means and Standard Deviations per Participant Background

	Background Type							
	University		Professional		Vocational		Total	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Job sat.	0.06	0.87	0.06	0.99	-0.05	1.06	0	1

Lines = order lines picked, errors = % orders with error(s), Job sat. = Job satisfaction, Dom. RF = Dominant regulatory focus (higher = more promotion focus, lower = more prevention focus)

We employed Analysis of Covariance (ANCOVA) in SPSS version 22 to investigate the predictors of job satisfaction. The full model (Table 11, model 3) did not yield any significant interactions between picking method and incentive condition for job satisfaction and dominant regulatory focus dominance did not appear to play role either. Based on these results we cannot conclude that the picking method, incentive system, or regulatory focus of order pickers impacts their job satisfaction. However, it is important to consider that constructs such as job satisfaction might not be impacted by relatively short-term tasks. It is therefore not ruled out that the investigated predictors will impact job satisfaction on the longer term.

Table 11: One-way ANCOVA. Dependent variable: Job Satisfaction

	Model 1		Model 2		Model 3	
Effects	F	Df	F	Df	F	Df
Fixed intercept	5.58*	1	4.13*	1	1.71	1
Age	0.125	1	1.24	1	1.00	1
Participant background	0.224	1	1.24	1	1.01	1
Picking experience	1.8	1	0.639	1	0.503	1
Education	0.536	1	0.64	1	0.859	1
Picking position 2	0.897	1	0.612	1	1.84	1
Picking position 3	4.37*	1	4.51*	1	3.24†	1
Picking method	2.98†	2	3.10*	2	0.965	2
Incentive condition			0.303	1	0.051	1
Method × condition			0.93	1	0.432	2
Dom. RF					0.992	1
Method x RF dominance					0.177	2
Condition × RF dominance					0.605	1
Meth. × cond. × RF dom.					0.079	2
R^2	0.139		0.156		0.193	
# of individual observations	110		110		110	

Dom. RF = Dominant regulatory focus (higher = more promotion focus, lower = more prevention focus)

** $p < .01$, * $p < .05$, † $p < .10$

Chapter 3

Pick One for the Team: The Effect of Individual and Team Incentives on Parallel and Zone Order Picking Performance

3.1 Introduction

Most warehouse employees spend a substantial amount of their time on the retrieval of products from storage locations in the warehouse. This task, order picking, is a costly process with a considerable influence on the productivity of the supply chain as a whole (Tompkins et al., 2010). The rise of e-commerce, of which the annual revenue has grown by nearly 20% worldwide between 2010 and 2014 (Statista, 2015), emphasized the need for cost-effective and productive order picking even more. Consequently, realizing improvements in the order picking process can help companies in increasing their competitiveness by reducing warehousing costs and raising the service level.

Order picking

The most commonly used order picking setup is *manual-pick picker-to-parts* picking, in which order pickers (De Koster, 2012) travel along the aisles of a warehouse to recover items. In alternative setups, such as in automated storage and retrieval systems (AS/RS) and man-aboard order picking systems, the performance of the system is mainly determined by formal aspects of the design of the systems such as the storage policy (Jarvis and McDowell, 1991; Petersen et al., 2004; Roodbergen and Vis, 2009), batching (Hsu et al., 2005; Pan and Liu, 1995), and warehouse design (Gu et al., 2010; Heragu et al., 2005). A characteristic distinguishing *manual picker-to-parts* picking from other order picking setups is the relatively large role of the order picker. System and warehouse design play a role in determining the maximally achievable performance in *manual-pick picker-to-parts* picking as well, but achieving a high output is still subject to human performance.

Picker-to-parts order picking can be executed using various picking methods. Two of the most commonly employed picking methods are parallel picking, in which every picker completes a single order from the beginning to the end independently, and zone picking, in which every order is handled by different pickers as it is passed on through zones in the warehouse. These methods can to a large extent be differentiated from each other in terms of the level of independence/interdependence of the work (Doerr et al., 2004; Schultz et al., 1998). That is, parallel picking methods seem to refer to tasks in which their performance is largely independent from the performance of others, while zone picking refers to tasks in which the performance of one worker is highly dependent on the performance of other workers. The effectiveness of parallel and zone picking depends heavily on warehouse layout, technology present in the warehouse etc. (De Koster et al., 2007; Hsieh and Tsai, 2006; Hwang and Cho, 2006). As a consequence different warehouses employ different picking methods.

The question that we ask ourselves is how companies can motivate workers, whether they work in parallel picking or zone picking systems, to optimize their picking performance. A commonly used method through which companies achieve higher worker motivation is by using an incentive system (Lawler III, 1990; Locke, 1968), and with right, since research testifies to the effectiveness of incentives (Condly et al., 2003; Jenkins and Gupta, 1981). Given that both parallel picking and zone picking systems are widely implemented though, this raises the important question of whether similar incentives are optimal for both picking systems. Below we argue that, based on their differences in terms of task interdependence, this is unlikely to be the case.

Incentive systems

Literature focusing on the behavioral aspects of job performance has consistently demonstrated that elements such as goal-setting (Locke et al., 1981) and financial incentives (Jenkins Jr et al., 1998) can be powerful methods to increase the performance of employees. Several meta-analyses have estimated a performance improvement between 20% and 30% resulting from the implementation of an incentive scheme (Condly et al., 2003; Jenkins Jr et al., 1998) Companies are well aware of the potential benefits of offering rewards and recognitions to their employees in return for achieving specific targets. Examples of the implementation of incentive structures are the recognition of an 'employee of the month', rewards for the best performing business unit, or company-wide profit sharing schemes.

One of the most important considerations in implementing incentive systems is whether the organization should implement an incentive system that is completely based on individual performance, or rather adopt a cooperation-based reward scheme in which the group performance determines at least part of the individual pay. Working in teams is increasingly prevalent in modern organizations, and individual incentive systems do not always fit well in that context (Zingheim and Schuster, 2000). Employees often have to execute interdependent tasks, and it can be difficult for a manager to evaluate the performance of an employee without considering the influence of direct colleagues (Dobbins et al., 1991). For example, studies have shown that incentives geared towards achieving high individual performance generally deliver better results in occupational settings characterized by independent work (Dobbins et al., 1991), whereas the effectiveness of team incentives has been demonstrated in settings with interdependent outcomes (Pritchard et al., 1988; Zingheim and Schuster, 2000). Given the differences in terms of interdependence between parallel and zone picking, we suggest that individual-based incentives work particularly well with an independent task such as parallel picking, whereas team-based incentives are especially effective in combination with more interdependent tasks such as zone picking.

Still, the research comparing the effect of different incentive systems on workers performance in companies is surprisingly scarce (Prendergast, 1998). In addition to this, some empirical findings did not show a difference between team-based pay schemes and individual-based pay schemes at all in different situations (Pfeffer, 1998). This provides a strong need to test these ideas in rigorous studies. Given that in order picking performance is generally defined on two dimensions, productivity (the amount of work done) and quality (the absence of errors in work) we expect these effects to be noticeable for both productivity and quality measures of work. These expectations are stated in the following hypotheses:

H1a: *Individual-based incentives will deliver higher productivity results in parallel picking than team-based incentives.*

H1b: *Individual-based incentives will deliver higher quality results in parallel picking than team-based incentives.*

H2a: *Team-based incentives will deliver higher productivity results in zone picking than individual-based incentives.*

H2b: *Team-based incentives will deliver higher quality results in zone picking than individual-based incentives.*

It is nonetheless difficult to validate these expectations in practice, as most warehouses only make use of a single incentive scheme in rewarding their employees. Comparisons or between warehouses (or different points in time in the same warehouse) could provide some general insights but may suffer from numerous potentially confounding variables such as warehouse layout, size, type of products handled, and differences in the workforce. To draw more rigorous and reliable conclusions, these confounding factors need to be controlled. This can be done best using laboratory experiments. Unfortunately, very few studies on incentive systems use laboratory experiments, and if laboratory experiments are used the setup is generally too abstract (i.e. not involving real effort or realistic tasks) to deliver results that are generalizable to practice (Van Dijk et al., 2001).

Using a laboratory experiment that represents a real order picking environment, this paper examines the differences in performance in terms of productivity and quality between team-based incentives and individual-based incentives in two different order picking methods: parallel picking and zone picking. The results obtained through rigorous approach contribute to the theory on incentive systems in OM by offering empirical evidence for existing theories. From a practical perspective, the results aid managers of warehouses and other occupational settings involving low-skilled labor in deciding which incentive systems might fit best with their specific situation.

3.2 Methodology

Participants

For this lab experiment data was collected from 63 participants arranged in 24 groups of two or three order pickers. Whether a team consisted of two or three order pickers was controlled for in the analyses. All participants were university students recruited through a notification on the university intranet and through emails to students enrolled in various courses. Each student was told that that they could earn between €5 and €15 for their participation, depending on performance. Of the 63 participants, 58.7% were male, and the average age of all participants was 22.8 years with 46% of them being aged between 17 and 22, and 54% being aged between 23 and 35 years old. 84.1% of the participants had no order picking experience at all, whereas 15.9% had at least one month of order picking experience.

Procedure

The experiment was executed in a laboratory room converted to a small order picking warehouse (Figure 3). Although this setup is of a different magnitude than the full-size warehouses commonly encountered in practice (and investigated in experiment 1), it should in many respects represent a compact warehouse used for the storage and picking of small-sized products. The setup consisted of three zones, being placed in an inverted U-shape. In this experiment the zones were all equally sized. Each zone consisted of 7 locations with two levels each. The locations were numbered according to the zone, location and level. For example, zone 1, location 4, level 2 is indicated by location number A1.4.2. Participants walked on the outside of the inverted U-shape to collect orders in small boxes. After completing a short questionnaire on demographics and some control variables, participants were given an explanation and executed a brief practice picking run. In zone picking, pickers were assigned to a zone based on their performance in the practice run. Subsequently, in the real picking run, participants had to pick as many orders with as few errors as possible in 40 minutes. They did this with an assigned picking method and incentive structure. The orders contained on average 8.8 order lines ($\sigma = 3.10$, log-normally distributed) and each order line prescribed the picking of one, two, or three units ($\mu = 1.45$). The pickers had to pick the right quantity of the correct product, and had to place a checkmark on their order list to confirm this. Every individual order line had to be confirmed directly after the particular pick. Once the order was finished, the experimenter checked the order for mistakes. After the stopwatch of the experimenter indicated that 40 minutes had passed, the participants stopped picking. To finish the experiment a short questionnaire had to be completed, after which the participants were debriefed and paid for their participation efforts. The total experiment took approximately 60 minutes.

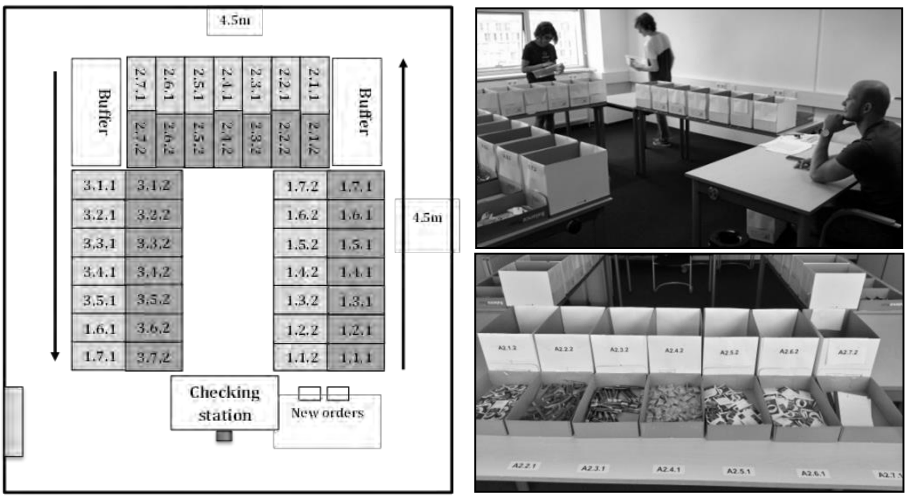

Figure 3: Laboratory warehouse layout (measures are in meters)

Manipulations

The lab experiment used a 2x2 between-subjects design with picking method and incentive conditions as independent variable.

Picking methods: The methods used were parallel picking and zone picking. In parallel picking all sides of the inverted U-shape together complemented a single line. In zone picking, each side of the inverted U-shape represented a zone. Two tables served as buffers between the three zones. In addition to the picking task, the first picker also had to write down the team number on the order list, and the last picker had to deliver the order to the checking station. The teams were randomly assigned to a combination of picking method and incentive condition.

Motivational incentives: 32 participants had to complete as many orders without errors as possible as a team (team-based incentive system). They were told that their performance was benchmarked against the results of teams that participated in an earlier experiment, and that they would earn between €5 and €15 based on their score on the benchmark. The other 31 participants focused on completing as many orders without errors individually (individual-based incentive system). Similarly, they were told that their score was benchmarked against individual results of earlier individual order pickers. The participants in the two incentive conditions were distributed among the two picking methods, as displayed in Table 12. In the end, all participants received the same amount of €15. The participants were not aware of this beforehand, as was confirmed afterwards with a control question.

Measures and covariates

Productivity was measured by the number of picked order lines during the 40 minutes of picking.

Quality was measured by the percentage of completed orders that contained errors. The experimenter checked every individual order.

Age, education, and *experience* with order picking of the participants were measured in the first questionnaire to be used as control variables. *Age* was measured in years, *experience* with order picking was measured in months, and *education* was measured by respondents indicating their highest completed level of five possible options: primary school, high school, vocational college, polytechnic institute or university. Dummy variables were used to control for potential influence of the zone number of participants in zone picking, the group size (two or three persons in parallel picking), and which one of the two experimenters executed the experiment (one experimenter conducted eighteen experimental sessions, the other experimenter was responsible for conducting six sessions).

3.3 Analyses and results

As initial step, we created an overview of the means and standard deviations per condition (Table 12). The control variables are not taken into account yet in the data displayed in this table, but it provides a rough overview of the patterns that can be found. Regarding productivity, the most striking difference appears to be the difference of approximately 30 picked lines per individual (approximately 11%) between zone picking with individual incentives and zone picking with group incentives. Regarding the quality, group incentives appear to deliver similar results in terms of the percentage of orders with errors in both parallel picking as well as zone picking, whereas individual incentives seem to be especially effective in zone picking. However, it should be taken into consideration that the standard deviations are relatively high.

Table 12: descriptive statistics and distribution of participants across conditions

Incentive	Outcome	Picking Method								
		Parallel			Zone			Total		
		N	Mean	Std. dev	N	Mean	Std. dev	N	Mean	Std. dev
Individual	Picked lines	14	307.4	39.6	18	269.6	22	32	286.2	35.8
	% orders with error	14	11.85	13. 23	18	6.42	6.2	32	8.8	10.09
Group	Picked lines	16	322.6	38.1	15	298.5	33.6	31	310.9	37.5
	% orders with error	16	8.75	6.5	15	8.94	11.79	31	8.85	9.27
Total	Picked lines	30	315.5	38.9	33	282.7	31	63	298.3	38.5
	% orders with error	30	10.2	10.13	33	7.57	9.1	63	8.82	9.62

To investigate the potential influence of the control variables on the outcome variables, a correlation table was created (Table 13). This table also displays the means and standard deviations of the control variables. In addition to this, the binary dummy variables for the zone positions, groups consisting of two pickers, and the experimenter are included in the correlation table. Because the number of picked order lines correlates with the dummy for the second position in the zone, the dummy for the groups with two pickers, and the dummy for the experimenter, we included those dummy variables in the model predicting order lines picked.

Table 13: Means, standard deviations, and Pearson correlations

Variable	Mean	Std. dev.	1	2	3	4	5	6	7	8	9
1 Picked order lines	298.34	38.46	-								
2 % of orders with errors	8.20%	9.60%	.12								
3 Gender	N/A	N/A	.09	.16	-						
4 Age	22.83	3.42	.10	.12	-.10	-					
5 Education (level 1-5)	3.80	1.50	-.03	.02	-.07	**.68***	-				
6 Experience (months)	1.27	5.85	.19	.04	-.01	-.02	-.03	-			
7 Zone position 2	N/A	N/A	**-.31***	-.03	-.13	-.05	.03	-.06	-		
8 Zone position 3	N/A	N/A	-.13	-.13	.21	.01	.03	-.09	-.21	-	
9 Two-picker group	N/A	N/A	**.33***	.10	-.03	**.32***	.01	.04	**-.29***	**-.29***	-
10 Experimenter	N/A	N/A	**-.28***	-.20	-.11	.04	.10	-.10	-.03	-.03	.03

Note: N = 63, *p < .05, N/A = not applicable

Subsequently, we used the steps explained by Bliese (2009) with the multilevel package in R 3.0.1 (R Core Team, 2013) to estimate the relative influence of the group-level on the outcome variables. The ICC(1) and ICC(2) of the outcome variables were calculated, and Random Group Resampling with 1008 pseudo groups was employed to examine the influence of the group-level. The ICC(1) and ICC(2) (Table 14) values demonstrate that a large proportion of the variance in order lines picked can be explained by the group level, whereas the group level only accounts for a small proportion of variance in the percentage of orders with errors. This is confirmed by the fact that the within-group variance of the real groups was significantly smaller than the within-group variance of the pseudo groups for the number of picked order lines, but not for the percentage of orders with errors. Therefore, the groups are taken into account by incorporating random intercepts in the model explaining the number of picked order lines, but not in the model explaining the percentage of orders with errors.

Table 14: Group-level properties

	ICC(1)	ICC(2)	RGR z-value	RGR p-value (one tailed)
1. Order lines picked	0.72	0.88	-3.23	<.01
2. % orders with errors	0.11	0.25	-0.27	0.39

Productivity: To confirm that a multilevel model is indeed the right approach, we compared a model without a random intercept with one that contained a random, group dependent intercept. These models were fit using the 'lme' and the 'gls' functions in the 'nlme' package (Pinheiro et al., 2013) in R 3.0.1 (R Core Team, 2013). For the random intercept model the -2 log likelihood value (632.63) was significantly larger than for the model without random intercept (986.59, $\Delta = 9.86$, $p < .01$. Consequently, a linear-mixed effects model was created to predict the number of lines picked while controlling for the influence of the position in the zone, two-picker groups, and who of the two experimenters conducted the experiment.

Table 15: Linear mixed-effects model. Dependent variable: picked order lines

Effects	Model 1 Wald χ^2	Df	Model 2 Wald χ^2	Df
Random (group) intercept	**1172.50****	1	**318.21****	1
Picking position 2	**5.76***	1	**4.81***	1
Two-picker group	**3.26**†	1	0.09	1
Experimenter	**3.81**†	1	**4.41***	
Method		1	**3.16**†	1
Incentive condition		1	0.05	1
Method × Incentive condition		1	1.12	1
Marginal R^2	0.22		0.34	
Conditional R^2	0.76		0.78	
# of groups	24		24	
# of individual observations	63		63	

** $p < .01$, * $p < .05$, † $p < .10$

The results, displayed in Table 15, show that when controlling for some potential covariates, the picking method has a substantial effect on the number of picked order lines. In the complete model the fixed factors explain 34% of the variance in picked lines, whereas the entire model (fixed factors + random intercept) explains 78% of this variance. Even though the incentive condition and the interaction of the incentive condition with the picking method do not appear to have a statistically significant effect, a plot (Figure 4) is employed to visualize the contrasts between the various conditions.

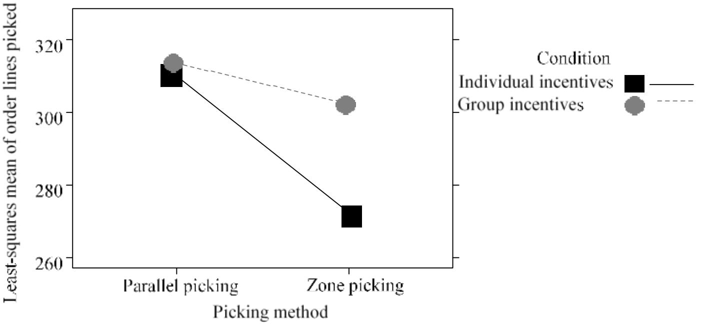

Figure 4: Interaction between picking method and incentive condition on productivity

Pairwise comparisons to test the one-tailed directional hypotheses reveal that group incentives (M = 302.32, SD = 14.21) perform substantially (approximately 11%) better than individual incentives (M = 272.39, SD = 13.17), in zone picking (p = .047), which is according to the expectations stated in hypothesis 2a. However, the difference between individual (M = 309.98, SD = 14.18) and group incentives (M = 313.66, SD = 13.73) in parallel picking seems negligible, which contradicts hypothesis 1a.

Quality: The ICC(1) and ICC(2) values and the RGR p-value of the percentage of orders with errors (Table 14) already suggested that the group level does not play a substantial role in predicting this outcome, which is confirmed by the difference in -2 log likelihood value between the model with and without random intercept (Δ = 1.08, p = .30). Therefore, to investigate the predictors of the percentage of orders with errors, a one-way ANCOVA was performed with the same set of control variables as in the productivity predicting model (Table 16). The full model explained nearly 10% of the variance in percentage of orders with errors, and the picking method appeared to be a marginally significant predictor.

Table 16: Linear mixed-effects model. Dependent variable: percentage of orders with errors

	Model 1		Model 2	
Effects	F	Df	Wald χ^2	Df
Fixed intercept	**26.83****	1	**17.56****	1
Picking position 2	0.054	1	0.45	1
Two-picker group	0.237	1	0.15	1
Experimenter	2.04	1	**3.01**†	1
Method		1	**3.66**†	1
Incentive condition		1	1.43	1
Method × Incentive condition		1	2.06	1
R^2	0.037		0.099	
# of groups	24		24	
# of individual observations	63		63	

** $p < .01$, * $p < .05$, † $p < .10$

Inspecting the plot of the least-squares means (Figure 5) shows that in terms of the percentage of orders with errors, no significant differences between group incentives and individual incentives exist in parallel picking (M = 13.5%, SD = 2.9% vs. M = 9.2%, SD = 2.8%) and zone picking (M = 5.4%, SD = 2.6% vs. M = 8.2, SD = 2.7). This suggests that, unlike the positive influence of individual incentives on quality in parallel picking that was hypothesized (H1b), an individual incentive system does not appear to benefit quality performance in parallel picking. Also, the finding that there are no significant quality differences between the two incentive structures in zone picking is not in line with hypothesis 2b.

Table 16: Linear mixed-effects model. Dependent variable: percentage of orders with errors

	Model 1		Model 2	
Effects	F	Df	Wald χ^2	Df
Fixed intercept	**26.83****	1	**17.56****	1
Picking position 2	0.054	1	0.45	1
Two-picker group	0.237	1	0.15	1
Experimenter	2.04	1	**3.01**†	1
Method		1	**3.66**†	1
Incentive condition		1	1.43	1
Method × Incentive condition		1	2.06	1
R^2	0.037		0.099	
# of groups	24		24	
# of individual observations	63		63	

** $p < .01$, * $p < .05$, † $p < .10$

Inspecting the plot of the least-squares means (Figure 5) shows that in terms of the percentage of orders with errors, no significant differences between group incentives and individual incentives exist in parallel picking (M = 13.5%, SD = 2.9% vs. M = 9.2%, SD = 2.8%) and zone picking (M = 5.4%, SD = 2.6% vs. M = 8.2, SD = 2.7). This suggests that, unlike the positive influence of individual incentives on quality in parallel picking that was hypothesized (H1b), an individual incentive system does not appear to benefit quality performance in parallel picking. Also, the finding that there are no significant quality differences between the two incentive structures in zone picking is not in line with hypothesis 2b.

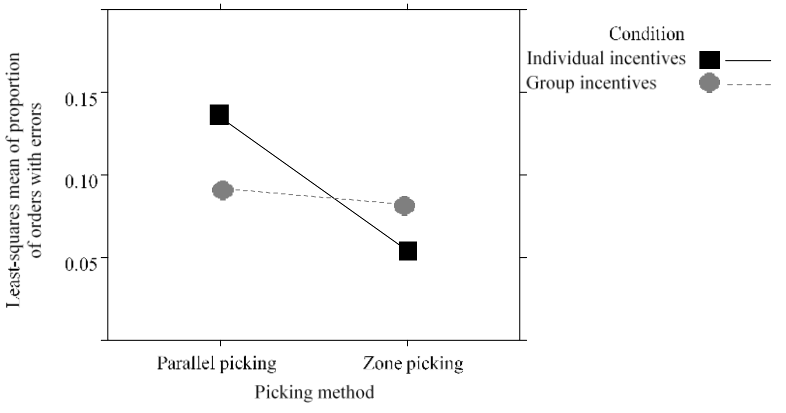

Figure 5: Interaction between picking method and incentive condition on quality

3.4 Conclusions

In this laboratory experiment we found that using team incentives (compared to individual incentives) leads to higher productivity in zone picking, but not lower productivity in parallel picking. Moreover, using team incentives (compared to individual incentives) does not affect quality of performance to a large extent.

Implications for theory

The results of the study confirm the expectation that team-based incentives deliver substantially higher productivity than individual-based incentives in zone picking. This is important, since it provides the first evidence that team incentives may match zone picking. The results do not confirm the expectations that for parallel picking, individual and team-based incentives delivered nearly identical productivity results. The absence of differences in productivity in parallel picking is surprising, because theory would suggest that more independent tasks such as parallel picking benefit from incentives focused on rewarding individual performance.

A possible cause for this finding could be the nature of the individual incentive structure in combination with the order picking environment. The expectations that team-based incentives should perform worse in parallel picking are partly based on the assumption that pickers are potentially working less hard with team-based incentives because of the free-riding problem. However, since in order picking all team members are working in the same environment where it is relatively easy to monitor each other, social pressure is probably mitigating this free-rider effect. Furthermore, with individual-based incentives, every participant is rewarded based on the work he or she completed. The earnings of these participants did not depend on their performance relative to their direct colleagues, but only on their performance relative to earlier participants. This absence of direct competition essentially creates similar objectives for participants with individual or team-based incentives: picking as many correct lines as possible without trying to do more to outperform other pickers or trying to do less to benefit from freeriding on the performance of the other pickers.

Another important finding is that our manipulation do not affect quality of performance. Reasons for this may be that errors simply occur too infrequently to really find effects (a ceiling effect) or that workers consider productivity to be the more important dimension of order picking performance. Be that as it may, this still suggests that team incentives provide better performance (higher productivity and negligibly worse quality) than individual incentives in zone picking systems. At the same time in parallel picking systems team incentives lead to similar performance (almost no difference in productivity and slightly better quality) than individual incentives. Altogether, this makes a good case for the use of team incentives in order picking.

Implications for practice

We provide an example of the potential impact of implementing these findings in practice, based on the data obtained in the experiment. Take a relatively small warehouse with 20 order pickers. According to a study among HR departments in the United States, the median expected salary for a typical order picker in the United States is $29,049 (Salary.com, 2013). This implies that the total annual salary costs for the order pickers in this situation are approximately $581,000. The following example shows the possible consequences of implementing the findings of the experiment.

Assume the warehouse uses a zone picking system combined with an individual-based incentive system. In this case, switching to a cooperation-based incentive system could increase productivity by 11% (Figure 6). This means that the same amount of work could be done by 18 pickers instead of 20 (20 / 1.11 = 18.0), leading to $58,098 (twice $29,049) in cost savings. Although this did not lead to a significant increase in errors at the same time, it would be even possible to employ one person as quality inspector and still achieve the same productivity with fewer employees (Figure 6).

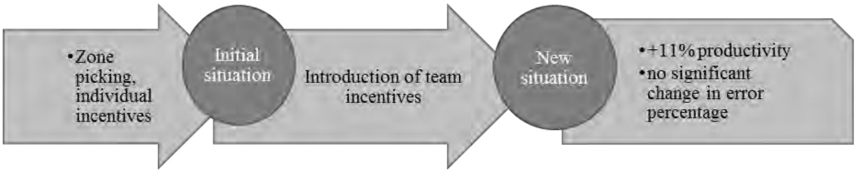

Figure 6: Example impact of aligning incentive system based on experiment results

Implementation

Most managers are already well aware of the fact that incentive systems are effective, and use incentive systems to increase productivity in their organizations. Still, the actual magnitude of the effects of such systems is often unknown, and also the differences in effectivity between different incentive systems are not always clear. By comparing a team-based with an individual-based incentive system, the current study addresses the latter issue. Based on the results of this study companies using a zone picking method should make sure to employ an incentive system geared towards team performance, such as making (part of) the wage dependent on the productivity of picking teams. The choice for a particular incentive system is less essential for companies using a parallel picking setup

Strengths and Limitations

We used a laboratory situation to have full control over the experimental manipulations in our design. This approach is a strength of this study, since a similar degree of control and academic rigor is practically impossible to achieve using a study in the field. However, like with all laboratory experiments, it is not certain to what extent our findings generalize to practice. Even though the experimental order picking task itself is very similar to the picking tasks that can be observed in real warehouses, the lab environment is obviously different. In a real warehouse people are potentially confronted with a more spacious environment, higher noise levels, and more distractions in general.

Also, even though we believe that 40 minutes of order picking is a relatively long time for an experimental task, the identified effects could work out differently in practice if pickers execute this task for eight hours a day, 40 hours a week, during multiple years. The impact of the incentive system might slowly vanish, and a potential need to re-emphasize the incentive system frequently could exist.

Furthermore, a larger number of participants would have been desirable to obtain more statistical power. 63 participants is a relatively small number for the 2x2 between-subjects design that we use. In addition this, only academic students participated to this experiment. In this context of a task involving physical labor, it is not sure whether students are a suitable representation of the order pickers normally working in warehouses.

Concluding, through a controlled laboratory experiment we have demonstrated that team incentives are strongly preferred over individual incentives in more interdependent tasks. This finding emphasizes that in choosing an incentive system it is essential for companies to carefully evaluate the type of task(s) that will be subject of the incentive system to achieve higher performance in terms of productivity or quality.

Chapter 4

Exploring the role of picker personality in predicting picking performance with pick by voice, pick to light, and RF-terminal picking.

4.1 Introduction

An essential activity in nearly every supply chain is the retrieval of products from their storage location in preparation of shipment to particular customers. Given that this process, order picking, can add up to approximately half of the total warehousing costs (Tompkins et al., 2010), many warehouses continuously investigate whether their order picking processes can be made more efficient. As a consequence, the material handling industry has introduced technological tools to facilitate easier picking for employees, and to increase picking productivity and quality. Examples of these tools are pick to light (PtL), pick by voice (PbV), and RF-terminal picking. These tools are already being used widely in many warehouses around the world, and have aided companies to realize substantial improvements in their order picking process.

However, even when advanced picking technologies such as PtL, PbV, or RF-terminal picking are employed, picking performance is still greatly dependent on the extent to which pickers are able to use these technologies efficiently. Therefore, it is of interest to investigate the influence of individual pickers and their interaction with the employed picking technology. Modern warehouses face increasing demands to deliver products as quickly as possible and without any mistakes (Frazelle, 2002), requiring from pickers that they can consistently work productively and accurately under high time pressure and with various picking tools. It is unlikely that all individuals respond equally well to these demands. To improve the order picking process, it is therefore interesting to find out which individual pickers can perform particularly well in specific order picking contexts.

One of the most important models used to distinguish individuals in terms of personality is the so called five-factor model, or Big Five (Digman, 1990). This model describes human personality using five dimensions: openness, conscientiousness, extraversion, agreeableness and neuroticism. Several of these dimensions have proved to be valid predictors of various job performance aspects (Barrick and Mount, 1991; Hurtz and Donovan, 2000). It is therefore likely that the order picking performance of an individual can be at least partly predicted by his or her personality, and that specific personality traits will fit better with particular picking tools and methods. This study aims to compare different order picking tools (RF-terminal picking, PbV, and PtL) in terms of productivity and quality performance, and explores the role of the Big Five personality traits in predicting picking performance. The study is carried out using an experiment in a full-size warehouse that was especially constructed for the purpose of order picking research, equipped to use all aforementioned picking tools. This approach should ensure a high degree of generalizability of the results to warehouse operations worldwide.

4.2 Literature review

Order picking

The most common order picking system is low-level picker-to-parts picking with multiple picks per route (De Koster, 2007). In this system, the order picker follows a route through the aisles, picking the items that are specified in the order on the way. These low-level picker-to-parts picking systems exist in many variants, and are the subject of this paper. The academic literature on low-level picker-to-parts picking systems is rich. Examples of aspects that have been investigated are the improvement of storage assignment strategies (Glock and Grosse, 2012), warehouse layout (Vaughan, 1999), picker routing (Petersen, 1999; Roodbergen and De Koster, 2001), physical properties of the SKU's and their locations (Finnsgård and Wänström, 2013), and combinations of these aspects (Chackelson et al., 2013). Low-level picker-to-parts systems have been subject to a considerable degree of technological development during the last decade. Where picking with these systems in the past typically only took place with the help of a paper picking list, pickers are now often aided by advanced technological tools that help them to maximize picking performance and reduce the chance of errors (Ten Hompel and Schmidt, 2006). Currently a number of modern technological tools are gaining ground in the warehousing sector. Examples are pick by vision (Schwerdtfeger et al., 2011), which makes use of head-mounted displays to support pickers with augmented reality, pick by tablet (Baumann et al., 2012), which uses a tablet computer with relevant information for the picker attached to the pick cart, and pick by point (Rudow, 2012), which uses a moving beamer to project a point at the appropriate picking locations. However, this paper focuses on three of the more mature and most widely used technological tools: RF-terminal picking, pick by voice (PbV), and pick to light (PtL).

RF-terminal picking is a paperless variant of picking with paper picking lists (Ten Hompel and Schmidt, 2006). The list of picking locations for a particular order is communicated to the picker through the display of the RF-terminal, which continuously communicates wirelessly with the warehouse management system (WMS). The terminal is commonly equipped with a barcode scanner. The picker has to scan the location before picking the required quantity of a product. This ensures that the picker is at the correct location. Picks are confirmed through the integrated keyboard of the terminal.

Pick by voice is a technology that makes use of audio and voice control to guide the picking process. The picker wears a headset that is connected to a small terminal that can be attached to his or her belt. This terminal communicates wirelessly with the WMS. Through the headset, the picker is informed of the location of the next item that has to be picked. The picker confirms the location through mentioning a unique check digit through the microphone, and then confirms the quantity of items picked. This process repeats itself until the order is completed and the next order is started. Most voice picking systems require a short training of the users, to enable that the system optimally adapts to their voice. However, the system used in our experiment did not require specific user profiles and could be used without such training. The individual setup of RF-terminals and PbV systems make these tools very suitable for use in a *parallel picking* setup, with pickers independently working on an order from start to finish.

Pick to light is a picking technology that supports the pickers with light signals. This technology is frequently applied in item picking applications, where pickers retrieve items from gravity flow racks or shelves (Sharp et al., 1996). A display with a light is attached to each storage location, lighting up when a product has to be picked from the particular location. The required quantity is shown on the display, and pickers confirm the pick by pressing a button. They continue working on an order until all lights have been turned off, after which a next order can be started. In our case, the PtL system was also equipped with zone displays, which show exactly how many locations a picker still has to visit in a particular zone and how many items still have to be picked. The location-based PtL displays make this tool more suitable to be employed in a sequential zone or dynamic zone setup to prevent multiple pickers from trying to pick the same item. In *sequential zone picking*, the warehouse or aisle is divided into zones that are connected through buffers or conveyors. Each picker is working in a particular zone, and he/she passes an order on to the picker in the subsequent zone when all products in his/her zone are picked, or places the order in a buffer. In *dynamic zone picking (bucket brigade picking)* the meeting point between the pickers determines the end of the zone. One picker will travel towards the upstream picker and the order will be transferred at the meeting point (De Koster et al., 2012; Tompkins et al., 2010).

In sum, it is in general possible to choose order picking tools and methods that are most suitable to fulfill the order picking demands of a specific warehouse. However, not only the particular demands and physical properties of the warehouse determine the performance of an order picking tool in a picker-to-parts setup. Order pickers have to use the picking tools, and individual differences between these order pickers can lead to individual differences in performance. Still, studies incorporating the characteristics of the people that actually work in the supply chain are relatively rare. The underexposure of this human aspect is especially poignant when considering that nearly every step in the supply chain involves human intervention and interaction, making people essentially the most important element of the supply chain (Keller and Ozment, 2009). Therefore, to improve supply chain performance in a world in which the potential contributions of investments in technology and infrastructure are becoming increasingly marginal, companies will have to focus more on the human aspect (Keller and Ozment, 2009). This certainly also applies to the warehousing and order picking steps in the supply chain. Most of the existing research on the influence of human aspects on supply chain outcomes focuses on the role of the manager in fostering performance (e.g. Richey et al. 2006; Malach-Pines et al. 2009). The role of lower-level employees such as order pickers, whose effort is ultimately determining whether a picker-to-parts picking system performs adequately, has hardly been investigated and provides still interesting research opportunities (Grosse et al., 2015). For instance, varying working conditions, boredom, and repetitiveness of specific tasks could influence performance of employees in order picking in different ways. Gaining more insight in how and to what extent individual differences among order pickers predict performance can help warehouse managers in assigning the right people to the right job. One of the most widely used concepts in distinguishing persons from each other is the notion of personality.

Personality

Although many ways exist to distinguish individuals from each other, most of the research on personality has converged towards the use of five robust factors to classify personality accurately (Digman, 1990). These five factors, which have been researched extensively, are labeled "Extraversion", "Agreeableness", "Conscientiousness", "Neuroticism", and "Openness". Some examples of traits that are associated with the five factors are provided by (Barrick and Mount, 1991). For example, people scoring high on *Extraversion* are generally seen as sociable, assertive, talkative, and active. People with a high score on *Neuroticism* are mostly regarded as anxious, depressed, angry, worried, insecure, and emotional. People scoring high on *Agreeableness* are commonly viewed as courteous, flexible, trusting, cooperative, forgiving, and tolerant. People rating high on *Conscientiousness* are usually seen as careful, thorough, responsible, organized, and persevering. People scoring high on *Openness* are in general regarded as being imaginative, cultured, curious, original, and broad-minded. Not surprisingly, numerous studies have investigated the relationship between personality and job performance. Although contradicting studies exist, recent meta-analyses have suggested that at least some personality aspects relate meaningfully to performance on the job (Guion, 2011).

The two traits that have been most consistently linked to job performance in all kinds of jobs are neuroticism (negative influence) and especially conscientiousness (positive influence) (Barrick et al., 2001). It is not surprising that people who can be characterized as careful, thorough, responsible, organized, and persevering perform better at nearly all jobs than people not possessing these characteristics. Similarly, being anxious, depressed, angry, worried, insecure, and emotional does not seem likely to be beneficial in any occupational context. Therefore, we expect to find a positive influence of conscientiousness on the order picking performance in terms of productivity and quality, and a negative influence of neuroticism on these performance indicators within the exploratory framework of this study. The other three traits have not been consistently linked to job performance, but can be beneficial in jobs that require specific skills (Barrick et al., 2001).

In the order picking context of this paper, one of these specific skills is teamwork. Participants working with PtL in a zone or dynamic zone picking method have to communicate and coordinate their actions to a certain extent. Agreeableness and extraversion have been identified as personality dimensions predicting performance in jobs that require interpersonal interaction and team performance (Barrick et al., 1998). Extraversion has been identified as a predictor of job performance in some contexts that requires teamwork (Mount et al., 1998), especially in predicting performance dimensions that are explicitly rewarded (Stewart, 1996). For order picking using PtL this finding would imply that more extravert and agreeable participants will perform better in terms of productivity and quality as long as these performance dimensions are specifically measured and rewarded.

4.3 Methodology

The following section describes the participants, the procedure, and the manipulations and measures used in the experiment.

Procedure

An experimental warehouse was designed and constructed especially for the purpose of research on order picking. Multiple material handling suppliers supported the project by supplying a PtL system, a PbV system, a RF-terminal picking system, picking carts, storage racks, product and location labels, dummy products, and two warehouse management information systems (WMSs) to control the various picking tools. 1000 labeled and colored wooden blocks with a volume between 0.2 and 2 liters and a weight between 50g and 500g served as dummy products. The blocks were placed at both sides of two identical aisles in the experimental warehouse, facilitating the execution of two experimental sessions simultaneously. Both aisles consisted of 10 sections with 2 levels, and 5 locations per level (Figure 1 in Chapter 2). The locations were numbered, equipped with barcodes, and labeled according to a logical system. For example, A02.4.2 refers to the location in aisle A, section 2, location 4, at the highest level. Orders were collected in crates (one crate per order) and transported on picking carts. A PtL system was installed in both aisles. Aisle A was being used for terminal picking, and voice picking took place in aisle B. We note here that due to the setup of the different picking technologies, which closely resembles their use in practice, the PtL technologies were only usable for a zone-picking or dynamic zone-picking task, while the RF-terminal technology and PbV technology were only usable with a parallel picking task. Although this makes the comparison of PtL with either RF-terminal or PbV less meaningful, we believe that investigating systems as we would encounter them in real life a very important part of this research design. The PtL system was provided by the company Pcdata (http://www.pcdata.nl), the PbV and RF-terminal picking systems were provided by the company Zetes (http://www.zetes.com). These companies took care of the installation, and provided all software and hardware necessary for the particular tools to work.

The pickers completed a pre-questionnaire including the Big Five measure, received an explanation of the particular picking tool, and then worked in a practice round of 10 minutes. The provided objective was to pick as many orders with as few errors as possible. Participants were incentivized to perform well by offering a prize (a €100 voucher of a media and electronics retailer) for the best 3 performing pickers of all participants. The set of orders was identical for all groups of participants, and contained 8.38 order lines per order on average ($\sigma = 2.35$, log-normally distributed). Each line prescribed the picking of a quantity of one or two product units ($\mu = 1.5$). The experimenter tracked the start and finish times of every individual order using a stopwatch. After completion, the order was checked for mistakes (wrong product or wrong quantity) by the quality inspector. The quality inspector was incentivized to check accurately by randomly double-checking the orders that he or she had inspected. After 10 minutes, the pickers returned the products to their original location. Subsequently, the pickers performed the real picking run. After the real picking run, pickers completed a short questionnaire and returned the blocks again. This full procedure was repeated in the second half of the experiment, with the pickers either using a different picking tool or a different picking method. The full experiment took approximately two hours to complete.

Participants

The experiment was executed with 101 participants, divided into 34 three-person picking teams. In one team, one of the pickers remained absent and was therefore replaced by a confederate of the experimenters. The individual results of this confederate were not included in the analyses. For every team, a fourth person was responsible for checking the quality of the completed orders. In 7 teams the quality of the orders was checked by a confederate of the experimenters, in the other teams a participant was responsible for checking the quality. For approximately 25% of the orders, the performance of the quality inspector was double-checked by the experimenters. These checks showed that the quality inspectors checked nearly perfectly. Of the 101 participants, 49 (37.6%) were students studying business administration at university level. 52 (40.6%) were professional warehouse workers, and 28 (21.8%) were students studying logistics at a vocational college. The differences in performance between these backgrounds can potentially provide insight in the learning curve and ease of use of the particular picking technologies.

An intranet notification was used to recruit the university students across various courses. All participating university students received €20 to compensate for their participation. A recruitment agency facilitated the participation of professional pickers of ten different companies to the experiment. They also received a €20 compensation. The vocational students were participating in the experiment for course credits.

Of the 101 participants with the role of order picker, 78.2% was male, 32.7% was aged between 16 and 20, 30.7% between 20 and 25, 16.8% between 25 and 32, and 19.8% was more than 32 years old. 54.5% of the pickers did not have any previous order picking experience, but 18.7% had worked as an order picker for at least one year. The majority of the participants (54.5%) consisted of Dutch native speakers, who completed the questionnaires in Dutch. 37.6% of the participants completed the questionnaires in English, and 7.9% (all of whom professional pickers) completed a Polish translation of the questionnaires.

Experimental design

Since PbV and RF-terminal picking is commonly used with parallel picking (every picker receives information about his or her own order on the terminal or headset) whereas PtL is usually employed with (dynamic) zone picking (every picker can observe all light signals for a particular order, but only picks the products in his or her zone), two separate studies are performed. In one study, 54 participants worked in a parallel setup with PbV for one run and for the other run with RF-terminals. In the other study, 47 participants worked with PtL in a zone setup for one run and with a dynamic zone setup for the other run. In both studies the sequence of conditions was balanced.

Outcome measures

The number of completed order lines per individual in the real picking runs served as the measures for picking productivity. The percentage of orders with errors (identified by the quality inspector) per individual during this real picking round represented the picking quality. Because some errors in a single order line can cascade into multiple errors across the entire order, this measure is preferred to a measure of the percentage of order lines that contains errors per individual. For pickers working in a zone or dynamic zone setup this percentage was representing only their own errors. Furthermore, the percentage was adjusted according to the share of the particular order that each picker completed (approximately one third) in order to facilitate an outcome that can be compared with the error percentage obtained in parallel picking.

Personality and control measures

Personality of the order pickers was measured using the Big Five Inventory (BFI) (Benet-Martinez and John, 1998; John et al., 1991, 2008; Table 14). The original English version of the BFI was used, but also the Dutch version (Denissen et al., 2008), and a Polish translation of the English version. A comparison between the reliability of the subscales between the different languages revealed no substantial differences. The reliability of the BFI subscales measuring Extraversion (α = .734), Agreeableness (α = .628), Conscientiousness (α = .780), Neuroticism (α = .814), and Openness (α = .634) was acceptable for use in exploratory research (Nunnally et al., 1967). The scores on the subscales were standardized before being used in the analyses.

The age of the participants (in years), order picking experience (in months), and their highest level of completed education (primary school, high school, vocational college, polytechnic institute, university, or other) were used as control variables. For PtL, the position of the picker in a particular zone might influence performance because the zones differ slightly in layout. To account for these differences, the zone in which a picker worked was included using dummy variables.

Table 17: BFI Items in English (John et al., 1991). E = Extraversion, A = Agreeableness, C = Conscientiousness, N = Neuroticism, O = Openness. "+" refers to an item that scores positively on the particular trait, "−" refers to a negatively scoring item.

I see myself as someone who…	**I see myself as someone who…**
1. Is talkative (E, +)	23. Tends to be lazy (C, −)
2. Tends to find fault with others (A, −)	24. Is emotionally stable, not easily upset (N, −)
3. Does a thorough job (C, +)	25. Is inventive (O, +)
4. Is depressed, blue (N, +)	26. Has an assertive personality (E, +)
5. Is original, comes up with new ideas (O, +)	27. Can be cold and aloof (A, −)
6. Is reserved (E, −)	28. Perseveres until the task is finished (C, +)
7. Is helpful and unselfish with others (A, +)	29. Can be moody (N, +)
8. Can be somewhat careless (C, −)	30. Values artistic, aesthetic experiences (O, +)
9. Is relaxed, handles stress well (N, −)	31. Is sometimes shy, inhibited (E, −)
10. Is curious about many different things (O, +)	32. Is considerate and kind to almost everyone (A, +)
11. Is full of energy (E, +)	33. Does things efficiently (C, +)
12. Starts quarrels with others (A, −)	34. Remains calm in tense situations (N, −)
13. Is a reliable worker (C, +)	35. Prefers work that is routine (O, −)
14. Can be tense (N, +)	36. Is outgoing, sociable (E, +)
15. Is ingenious, a deep thinker (O, +)	37. Is sometimes rude to others (A, −)
16. Generates a lot of enthusiasm (E, +)	38. Makes plans and follows through with them (C, +)
17. Has a forgiving nature (A, +)	39. Gets nervous easily (N, +)
18. Tends to be disorganized (C, −)	40. Likes to reflect, play with ideas (O, +)
19. Worries a lot (N, +)	41. Has few artistic interests (O, −)
20. Has active imagination (O, +)	42. Likes to cooperate with others (A, +)
21. Tends to be quiet (E, −)	43. Is easily distracted (C, −)
22.. Is generally trusting (A, +)	44. Is sophisticated in art, music or literature (O, +)

4.4 Results

Since we cannot compare PtL with either PbV or RF-terminal due to the differences in picking methods, we first detail the results for the PbV and RF-terminal picking tasks and then continue with the results for PtL.

Pick by voice and RF-terminal

Descriptives: Firstly, a table with correlations and descriptives of the key variables and their correlations was created (Table 18). Also, the marginal means (controlling for picking experience, highest completed level of education, age, and the background of the participants) were calculated. Pairwise comparison between the controlled marginal means of the number of order lines picked with RF-terminal picking (*M* = 40.24, *SD* = 2.85) and PbV (*M* = 45.08, *SD* = 2.80) revealed that PbV is significantly more productive, on average 12%.

Table 18: Correlations between key variables and performance of picking with voice and RF-terminal

Variable	Mean	Std. dev.	1	2	3	4	5	6	7	8	9	10	11	12
1 Order lines RF-terminal	41.00	15.19	-											
2 Order lines voice	44.66	14.01	.66*	-										
3 Error percentage terminal	6.19%	15.00%	-.09	-.18	-									
4 Error percentage voice	4.86%	13.16%	-.06	-.07	.49*	-								
5 BFI: Neuroticism	0.00	1.00	-.09	.03	.43*	.51*	*.814*							
6 BFI: Extraversion	0.00	1.00	.19	.07	.03	-.18	-.49*	*.734*						
7 BFI: Openness	0.00	1.00	.12	-.09	.12	.04	-.13	.41*	*0.63*					
8 BFI: Conscientiousness	0.00	1.00	.34*	.23	-.19	-.26†	-.43*	.36*	.16	*0.78*				
9 BFI: Agreeableness	0.00	1.00	.10	-.14	-.19	.00	-.42*	.11	-.17	.34*	*0.63*			
10 Picking experience (months)	54.50	111.36	.21	-.07	.03	-.09	-.32*	.17	.08	.25†	.29*	-		
11 Education (level 1-5)	3.35	1.25	-.02	.13	.11	.18	.11	-.24	-.15	-.17	.04	-.14	-	
12 Age	28.41	11.29	.08	-.11	.18	.03	-.15	.03	.04	.36*	.21	.59*	.14	-

Note: *N* = 54 participants worked with voice- and RF-terminal picking. Pairwise deletion of missing values employed, resulting in a lower N for some correlations.
Cronbach's α is displayed in italics on the diagonal of the relevant variables.
† $p < .10$
*$p < .05$

Pairwise comparison between the controlled marginal means of the error percentage of RF-terminal picking (*M* = 5.6%, *SD* = 2.9%) and voice picking (*M* = 4.4%, *SD* = 2.6%) revealed that voice picking produces on average 21.4% less errors, but this difference is not significant (using p = .05). The correlation table (Table 18) also provides information about the relationship of the BFI personality traits and control variables with the performance of voice- and RF-terminal picking. We further investigated these correlations using repeated-measures analyses of variance (ANOVA) in SPSS version 20.0 (IBM Corp., 2012). Before the personality traits were added, we tested a model with the control variables age, education, picking experience, participant background (dummy variables, university students serving as reference group) and sequence of testing (if a participant started with terminal picking this dummy variable took the value of 1, otherwise the value was 0) as control variables to predict the number of order lines picked per individual using RF-terminal and PbV (Table 19). The picking tool was included as within-subjects factor in the analysis. Since we only have two different tools, problems of sphericity of variance cannot arise.

Within-subjects effects: When predicting the number of picked order lines, no significant main effect of tool emerged for PbV or RF-terminal. However, there were interaction effects between the picking tool and openness and between the picking tool and conscientiousness (Table 19). This shows that the personality traits openness and conscientiousness had different effects on the number of order lines picked depending on which picking tool was used. To explore this interaction further, two multiple regression analyses were performed using the same set of predictor variables to separately predict the number of order lines picked with PbV or RF-terminal (Table 20). This revealed that openness had a mildly positive effect for RF-terminal picking, whereas the effect was almost exactly the opposite for PbV. However, both of these main effects are not significant. Conscientiousness on the other hand did not seem to play a role in predicting the productivity performance of terminal picking, but displayed a strong and significant positive influence on PbV productivity. To explore the nature of this effect, the marginal means were compared between groups based on the percentile scores on conscientiousness. This revealed that especially the quintile of participants scoring the lowest on conscientiousness were less productive in terms of order lines picked (M = 34.31, SD = 5.21) than the participants in the second (M = 48.89, SD = 5.53), third (M = 51.09, SD = 5.75), fourth (M = 51.07, SD = 4.36), and fifth quintile (M = 45.48, SD = 5.51). This suggests that it is important to make sure that order picking employees possess a certain minimum level of conscientiousness. Conscientiousness levels much higher than this minimum offer only limited added value in terms of productivity.

Table 19: Repeated-measures ANOVA within-subjects effects for pick by voice & RF-terminal

	Model 1 Terminal		Model 2 Terminal		Model 1 Voice		Model 2 Voice	
Effects	Beta	t	Beta	t	Beta	t	Beta	T
Sequence (first terminal=1)	-.526**	-2.88	-.453*	-2.15	-.278	-1.645	-.135	-.774
Professional background	.494*	2.10	.554†	2.02	.158	.739	.195	.836
Vocational background	.312†	1.71	.268	1.35	-.020	-.116	.068	.369
Age	-.191	-.959	-.259	-1.11	-.265	-1.319	-.449	-2.18*
Education	.069	.377	.085	.426	.111	.616	.210	1.19
Picking Experience	.190	.816	.214	.838	.089	.410	.137	.649
BFI: Neuroticism			.182	.752		.199	.188	.954
BFI: Extraversion			.015	-.528		.178	.134	.647
BFI: Openness			.216	1.35		-.200	-.200	-1.12
BFI: Conscientiousness			.160	.887		.505	.512	2.67*
BFI: Agreeableness			.033	.162		-.226	-.233	-1.24
R^2	.295		.380		.093		.292	
Adjusted R^2	.149		.096		-.054		.049	
ΔF	2.20		.661		.631		1.80	
ΔR^2 significance	.095		.657		.704		.140	
# of observations	45		35		53		43	

** $p < .01$, * $p < .05$, † $p < .10$

Furthermore, the regressions show that sequence has a stronger effect for RF-terminal picking than for voice picking, which suggests that pickers can benefit from the voice picking experience when using RF-terminals, but not the other way around. Also, age proved to have a significant negative influence on the number of order lines picked with voice picking, implying that this technology is more difficult to use for older people. The R^2 values obtained through the multiple linear regression analysis reveals that the control variables (sequence, background, age, education and picking experience) explain nearly 30% of the variance in picking productivity using RF-terminals. The BFI personality traits explain another 8.5%. For PbV, only 9.3% of the variance is explained by the control variables, but the personality traits account for another 19.9%. This suggests that especially when employing PbV, taking the personality of the employees into account can make a difference in productivity performance.

Table 20: Multiple Linear Regression Results. Dependent variable: # of order lines picked per individual

	# Of Order Lines Picked			% of orders with error(s)		
Effects	*MS*	*Df*	*F*	*MS*	*Df*	*F*
Tool (Voice or RF-terminal)	18.32	1	.337	.000	1	.011
Tool * Sequence (first terminal = 1)	41.63	1	.765	.004	1	.335
Tool * Professional background	6.99	1	.128	.039	1	2.97†
Tool * Vocational background	.780	1	.014	.002	1	.120
Tool * Age	108.4	1	1.99	.015	1	1.14
Tool * Education	129.0	1	2.37	.003	1	.228
Tool * Picking experience	.685	1	.013	.003	1	.203
Tool * BFI: Neuroticism	17.12	1	.315	.000	1	.001
Tool * BFI: Extraversion	17.69	1	.325	.020	1	1.52
Tool * BFI: Openness	165.83	1	3.05†	.001	1	.083
Tool * BFI: Conscientiousness	245.24	1	4.51*	.004	1	.283
Tool * BFI: Agreeableness	83.34	1	1.53	.015	1	1.17
Error df		23			23	
# of observations		45			45	

** $p < .01$, * $p < .05$, † $p < .10$

The repeated measures ANOVA on the percentage of orders with errors revealed only a marginally significant interaction between tool and a professional background. Exploration of this interaction effect showed that professional order pickers performed significantly better than university students when picking with RF-terminals ($\beta = -.562$, $p < .05$), but not with PbV ($\beta = -.059$, $p = .786$). Apparently, for PbV picking experience is not important in achieving quality performance. Alternatively, professional pickers were trained in RF-terminal picking, but not in PbV picking.

<u>Between-subjects effects</u>: Inspection of the between-subjects effects revealed that the sequence in which the picking tools were used, the age of the participants (negative effect), and conscientiousness (positive effect) were marginally significant predictors of the number of order lines picked (Table 21). Of the Big Five personality traits, extraversion and especially neuroticism are the only variables individually accounting for a substantial part of the variance in the error percentage. Both of these personality traits are related to a higher percentage of orders with errors. Exploring this effect by comparing the marginal means of

quintiles of the participants' scores on neuroticism and extraversion reveals that neuroticism is especially detrimental in the highest quintile. These people make on average approximately twice as many errors as the participants in the lower four quintiles, for both PbV (quintile 1: M = 1.2, SD = 5.6, q2: M = 0.6, SD = 4.6, q3: M = 3.4, SD = 5.3, q4: M = 6.5, SD = 5.0, q5: M = 14.0, SD = 5.3) and RF-terminal picking (quintile 1: M = 1.5, SD = 4.9, q2: M = 0.3, SD = 4.3, q3: M = 10.8, SD = 4.1, q4: M = 2.8, SD = 4.3, q5: M = 23.2, SD = 4.7). In RF-terminal picking, the lowest (M = 9.3, SD = 6.6) and highest (M = 6.3, SD = 7.7) quintiles of participants in terms of extraversion scores make more errors than the second (M = 2.0, SD = 7.3), third (M = 5.2, SD = 6.1), and fourth (M = .45, SD = 7.4) quintiles. In PbV the pattern is opposite: The participants in scoring in the second (M = 8.1, SD = 5.5) or third quintiles (M = 9.5, SD = 4.8) of extraversion perform slightly worse in terms of error percentages than the participants with a low level (M = 5.4, SD = 5.8), but the participants scoring in the two highest quintiles on the extraversion scale produce the lowest error percentage (q4: M = 3.4, SD = 5.9, q5: M = 0.3, SD = 6.4).

Table 21: Repeated-measures ANOVA between-subjects effects for pick by voice & RF-terminal

	Order Lines			Errors		
Effects	*MS*	*Df*	*F*	*MS*	*Df*	*F*
Sequence (first terminal = 1)	1123	1	4.042†	.055	1	2.941†
Professional background	1395	1	5.021*	.198	1	10.63**
Vocational background	455.2	1	1.638	.002	1	.084
Age	1000	1	3.600†	.099	1	5.351*
Education	524.4	1	1.888	.003	1	.166
Picking experience	379.4	1	1.365	.000	1	.016
BFI: Neuroticism	92.98	1	.335	.467	1	25.10**
BFI: Extraversion	55.42	1	.199	.150	1	8.071**
BFI: Openness	148.8	1	.535	.010	1	.535
BFI: Conscientiousness	916.8	1	3.300†	.014	1	.759
BFI: Agreeableness	44.07	1	.159	.051	1	2.728
Error df	23			23		
# of observations	45			45		

** p < .01, * p < .05, † p < .10

In sum, some of the individual characteristics of pickers have a substantial effect on picking performance, but this effect differs between PbV and RF-terminal picking. In terms of productivity, especially warehouses working with PbV can benefit from taking individual differences in age and Conscientiousness (especially lower levels) into consideration. In terms of quality, Extraversion and Neuroticism generally relate to the error percentage, but this effect is dependent on the tool and specific score of the employee on these personality traits.

Pick to light zone and dynamic zone

<u>Descriptives:</u> A table with the correlations and descriptives of all variables involved (Table 22) was also created for the study on PtL. The marginal means (again controlling for age, education, and picking experience of the participants) of the number of order lines picked per participant background reveal that the overall marginal means are similar for zone picking (*M* = 61.97, *SD* = 2.47) and dynamic zone picking (*M* = 59.59, *SD* = 2.53). In terms of the percentage of orders with error(s), the estimated marginal means reveal that PtL in a zone setup (*M* = 19.6%, *SD* = 3.2%) performed better on average than PtL using a dynamic zone setup (*M* = 30.9%, *SD* = 3.9%) for participants of all backgrounds (*p* = .012). Again, repeated-measures analyses of variance (ANOVA) in SPSS version 20.0 (IBM Corp., 2012) were used to further investigate the data.

Table 22: Correlations between key variables and performance of pick to light

Variable	Mean	Std. dev.	1	2	3	4	5	6	7	8	9	10	11	12
1 Order lines light zone	61.11	15.46	-											
2 Order lines light dynamic	61.07	15.98	.63*	-										
3 Error percentage light zone	18.40%	22.52%	.13	-.03	-									
4 Error percentage light dynamic	27.06%	27.18%	.16	-.06	.42*	-								
5 BFI: Neuroticism	0.00	1.00	-.20	-.15	.37*	.10	*.814*							
6 BFI: Extraversion	0.00	1.00	.13	-.01	-.18	-.25	-.45*	*.734*						
7 BFI: Openness	0.00	1.00	.23	-.07	-.06	.01	-.09	.33*	*0.63*					
8 BFI: Conscientiousness	0.00	1.00	.23	.03	-.07	-.06	-.30†	.41*	.62*	*0.78*				
9 BFI: Agreeableness	0.00	1.00	.29†	.20	-.23	-.40*	-.33*	.45*	.34*	.57*	*0.63*			
10 Picking experience (months)	16.72	38.50	.03	-.19	-.15	.21	-.11	.29†	.34*	.38*	.09	-		
11 Education (level 1-5)	3.00	1.28	-.11	.09	-.21	-.28†	-.11	.05	-.05	-.24	-.02	-.17	-	
12 Age	24.89	9.36	-.04	-.16	-.28†	.24	-.09	-.04	.07	.31*	.03	.49*	-.09	-

Note: N = 47 participants worked with pick to light in a zone and a dynamic zone setup. Pairwise deletion of missing values employed, resulting in a lower N for some correlations.

Cronbach's α is displayed in italics on the diagonal of the relevant variables.

† $p < .10$

* $p < .05$

<u>Within-subjects effects:</u> a significant main effect of the picking method emerged, with dynamic zone picking producing a significantly higher percentage of orders with errors than regular zone picking. Furthermore, a significant interaction between the picking method and BFI personality trait neuroticism was identified (Table 23). Exploring this interaction using two separate multiple regression analyses (Table 24) revealed that neuroticism related to a higher percentage of orders with errors in zone picking, but not in dynamic zone picking. However, this effect was not significant on a 5% level and therefore not explored further. Furthermore, the regression table (Table 24) also reveals that whereas the control variables explain a substantial part of the variance in percentage of errors for zone and dynamic zone PtL (81.8% and 70.3% respectively), the added predictive value of the personality traits is limited (2.7% and 1.4% respectively) for PtL.

Table 23: Repeated-measures ANOVA within-subjects effects for pick to light

	Order Lines			Errors		
Effects	*MS*	*Df*	*F*	*MS*	*Df*	*F*
Method (Zone or Dynamic zone)	.123	1	.002	.117	1	5.393*
Method * Sequence (first zone = 1)	246.9	1	3.765†	.047	1	2.153
Method * Picker 2	7.264	1	.111	.066	1	3.048†
Method * Picker 3	17.65	1	.269	.038	1	1.739
Method * Professional background	76.85	1	1.172	.070	1	3.233†
Method * Vocational background	226.9	1	3.461†	.019	1	.867
Method * Age	.192	1	.003	.039	1	1.794
Method * Education	43.32	1	.661	.029	1	1.354
Method * Picking experience	62.89	1	.959	.003	1	.154
Method * BFI: Neuroticism	47.96	1	.732	.112	1	5.188*
Method * BFI: Extraversion	.105	1	.002	.001	1	.055
Method * BFI: Openness	11.38	1	.174	.066	1	3.033
Method * BFI: Conscientiousness	4.461	1	.068	.068	1	3.135†
Method * BFI: Agreeableness	3.164	1	.048	.025	1	1.136
Error df		16			16	
# of observations		41			41	

** $p < .01$, * $p < .05$, † $p < .10$

Between-subjects effects: The between subjects results (Table 25) did not reveal surprising results for the number of order lines picked or the percentage of orders with errors, since only some control variables appeared to have a significant influence. Also, pickers with a vocational background picked a significantly and substantially higher percentage of orders with errors than university students.

Summarizing, individual characteristics of order pickers seem to play a limited role in predicting order picking performance with PtL. The main finding concerns the negative relation between Neuroticism and quality performance.

Table 24: Multiple Linear Regression Results. Dependent variable: % of orders with errors per individual

	Model 1 Zone		Model 2 Zone		Model 1 Dynamic Zone		Model 2 Dynamic Zone	
Effects	Beta	t	Beta	t	Beta	t	Beta	t
Sequence (first zone =1)	-.278	-1.64	-.187	-.959	-.410*	-2.39	-.494*	-2.39
Picker 2	.087	.496	.220	1.10	-.261	-1.44	-.257	-1.36
Picker 3	-.014	-.081	.051	.272	-.281	-1.59	-.290	-1.57
Professional background	-.001	-.002	-.138	-.552	.191	.913	.410	1.547
Vocational background	.645**	3.85	.470*	2.34	.718**	4.09	.772**	3.60
Age	-.176	-.833	-.102	-.463	-.310	-1.48	-.374†	-1.74
Education	-.071	-.470	.031	.183	-.164	-1.05	-.227	-1.33
Picking Experience	-.029	-.179	-.019	-.098	.104	.645	.070	.373
BFI: Neuroticism			.316†	1.74			-.179	-1.00
BFI: Extraversion			-.004	-.022			.081	.382
BFI: Openness			-.191	-.876			.157	.783
BFI: Conscientiousness			.339	1.18			-.314	-.985
BFI: Agreeableness			-.076	-.356			-.243	-1.13
R^2	.818		.845		.703		.717	
Adjusted R^2	.334		.310		.386		.397	
ΔF	3.13		.817		3.44		1.08	
ΔR^2 significance	.013		.551		<.01		.404	
# of observations	45		45		41		41	

** $p < .01$, * $p < .05$, † $p < .10$

Table 25: Repeated-measures ANOVA between-subjects effects for pick to light

	Order Lines			Errors		
Effects	*MS*	*Df*	*F*	*MS*	*Df*	*F*
Sequence (first zone = 1)	243.5	1	2.739	.208	1	3.455†
Picker 2	2668.4	1	30.01**	.005	1	.080
Picker 3	301.8	1	3.394†	.044	1	.737
Professional background	134.3	1	1.511	.005	1	.090
Vocational background	84.89	1	.955	.590	1	9.813**
Age	100.8	1	1.134	.065	1	1.084
Education	153.3	1	1.724	.018	1	.298
Picking experience	51.79	1	.582	.006	1	.097
BFI: Neuroticism	25.72	1	.289	.007	1	.112
BFI: Extraversion	15.11	1	.170	.000	1	.006
BFI: Openness	39.82	1	.448	.014	1	.229
BFI: Conscientiousness	.134	1	.002	.002	1	.033
BFI: Agreeableness	46.88	1	.527	.029	1	.482
Error df		16			16	
# of observations		41			41	

** $p < .01$, * $p < .05$, † $p < .10$

Differences between backgrounds

Inspection of the results per participant background reveal similar patterns of results for professionals, university students, and vocational students. However, the absolute numbers show that, even after controlling for order picking experience, professional order pickers manage to consistently score relatively high on the number of order lines picked, while managing to score low on the percentage of orders with errors. This suggests that, regardless of the initial learning curve of a particular picking technology, it is possible to combine productivity with accuracy in a professional setting. Additionally, this results suggests that researchers have to be careful in employing students as participants in experiments involving aspects such as physical work. The patterns of results that emerge could be generalizable, but the absolute magnitude of the identified effects could be highly inaccurate. Differences between male and female pickers were not identified, but it should be noted that the relatively low number of female participants (22) was too low to facilitate a proper comparison with sufficient statistical power.

4.5 Implications

The results of this experiment provide managers with insights in the type of people that are suitable to achieve higher productivity and quality in order picking with particular picking tools and methods. Taking the findings into consideration can aid managers in achieving higher performance without necessarily incurring substantially higher costs.

Voice vs. RF-terminal: In our experimental setup, voice picking performed better than RF-terminal picking in terms of both productivity and quality. Other key insights include that for voice picking and RF-terminal picking, extraversion, neuroticism, and age are individual characteristics that relate to the percentage of picked orders with errors. Some interesting differences between the two picking tools were identified as well: for RF terminal individual differences did not predict productivity, but for voice picking more conscientious pickers were in generally more productive, and older pickers appeared to be less productive. The different effects of conscientiousness (and differing effects of other personality traits in general) could be explained by trait activation theory, which explains the situational specificity of the relationship between personality and job performance (Tett and Burnett, 2003). According to this theory, employees scoring high on conscientiousness are especially triggered by situational features of their job relating to precision, rule following and precise and explicit communications. These features seem prominently present in pick by voice, which requires high levels of attention, strict procedures, and precise voice commands in order to make the system work. More conscientious pickers are therefore likely to be particularly triggered by a PbV environment, motivating them to perform well. An important explanation of the different effects of age is the fact that hearing ability (Liu and Yan, 2007) and multitask performance (Riby et al., 2004) generally deteriorate with age. Correctly hearing spoken commands and being able to simultaneously execute picks and listen to information about subsequent picks is essential in PbV, which leads to a stronger influence of age on the performance with this picking tool

Pick to light zone vs. dynamic zone: For professional pickers PtL in a dynamic zone setup yielded higher productivity (without an effect on quality) than PtL in a regular zone setup. This difference was reversed for university students and vocational students. The only remaining identified significant effect of an individual characteristic was the negative relation between neuroticism and quality performance in zone picking. The fact that the other examined individual characteristics (besides background) do not influence picking performance with PtL suggests that effective use of this tool is equally accessible to anyone. This can probably be attributed to the simplicity of using pick to light, since no complicated commands or difficult key combinations need to be mastered.

Another finding that applies to all of the investigated methods and tools concerns the differences in performance between participants of different backgrounds (professionals, university students, and vocational students). The fact that professional pickers manage to be relatively productive with a relatively low error percentage suggests that it is possible to achieve decent performance using any of the tested picking tools and methods, as long as the users are reasonably trained and experienced.

The results suggest that neuroticism and extraversion and the age of the picker relate to quality performance in PbV and RF-terminal picking. A higher level of neuroticism also negatively relates to quality for PtL in a zone setup, and a higher age negatively impacts productivity in PbV. Contrastingly, PbV productivity is positively influenced by a higher level of conscientiousness. These insights can be considered by managers when assigning employees to work with a particular picking tool or method, in selecting a suitable picking method to be used by the order pickers already working in the company, or in identifying which pickers might particularly benefit from additional training. Since an overview of the BFI personality traits of an individual can be obtained through a questionnaire, managers could incorporate this information with relative ease.

4.6 Conclusions

To our best knowledge, this study is unique in incorporating individual differences in assessing the performance of various order picking tools and methods. Like all studies, this study is also subject to several limitations. For example, the sample size is relatively small and the experimental duration of 10 minutes per run is short. In the future it would be interesting to execute a similar study with a longer duration, to also facilitate the examination of the influence of long-term effects such as boredom and the repetitiveness of tasks. Furthermore, it would be worthwhile to investigate to what extent the findings regarding the influence of individual differences generalize to the latest generation of picking tools. The results of the current experiment show that taking these individual differences into account can aid substantially in predicting picking performance and, consequently, optimally designing the picking process. Having used a controlled field experiment with academic students as well as vocational students and professional order pickers has provided us with the opportunity to come up with several interesting findings that are generalizable to practice, but based on a methodically rigorous approach.

4.7 Acknowledgements

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Chapter 5

Safety Does Not Happen By Accident: Antecedents to a Safer Warehouse.

5.1 Introduction

Occupational accidents pose a serious risk to employees, companies, and to society as a whole. Fatalities, physical and mental injuries, employee absence, and legal action are only a subset of the consequences of occupational accidents. Despite the obvious necessity to reduce accidents at work, occupational accidents still happen quite frequently. In the United States alone, every year more than 4,000 employees suffer a fatal accident at work (Bureau of Labor Statistics, 2014). Worldwide, every day approximately 5,330 people die and 960,000 workers are hurt due to occupational accidents (Hämäläinen et al., 2009). The fatality rate is especially high among blue collar workers in the transportation and warehousing sector. For example, in the U.S., the fatality rate in this sector is 13.1 annual fatalities per 100,000 employees, approximately four times the average fatality rate in the country (Bureau of Labor Statistics, 2014). The current study focuses on factors that improve occupational safety in the warehousing sector.

Safety has been investigated from various perspectives. For example, Petersen (1989) emphasized the role of the physical working environment in fostering occupational safety. In contrast, many studies have also emphasized the importance of behavioral aspects including sleeping difficulties (Åkerstedt et al., 2002) and stress (Cooper and Cartwright, 1994) in understanding differences in operational outcomes such as safety. Barling et al. (2002) developed and empirically supported a model that relates safety-specific transformational leadership (SSTL) to occupational safety. De Koster et al. (2011) tested this relation in the context of warehouses, and demonstrated that it was even stronger than the effects of a wide spectrum of hazard reducing systems (HRS) present in warehouses. This puts SSTL in a central place for studying and managing warehouse safety. Unfortunately, knowledge of the role of SSTL beyond its effect on accidents is missing. We aim to contribute to the body of knowledge on SSTL in two ways.

This paper first examines the antecedents of SSTL. More insight into antecedents is very important for practice, because organizations need this information to select and develop potential managers to lead through SSTL. However, due to its emphasis on safety, SSTL differs from other leadership styles addressed in the literature and prior knowledge of antecedents of leadership may not be relevant in the case of SSTL. As a consequence, new theory should be developed to understand the antecedents of SSTL. We propose that a manager's dispositional prevention focus, a self-regulatory strategy focused on safety, security, and on the avoidance of mistakes and errors (Crowe and Higgins, 1997; Higgins, 1998, 1997), is a critical predictor of SSTL.

Secondly, we examine the outcomes of SSTL beyond safety, and investigate the impact of SSTL on other operational performance measures. Scholars have suggested that SSTL's focus on safety may also impact operational outcomes such as productivity and quality, but empirical evidence for this is limited. We expect that SSTL's emphasis on working more accurately and vigilantly makes employees require more time to complete tasks, leading to lower productivity (Förster et al., 2003). On the other hand, this focus on accuracy is likely to relate to a higher level of production quality as well.

By investigating SSTL's antecedents and the way it impacts other company performance outcomes, this study extends the research on SSTL. The importance of SSTL for safety has been established in research (Barling et al., 2002; Kelloway et al., 2006), but safety is commonly operationalized using self-reports that are potentially subject to social desirability response bias. De Koster et al. (2011) demonstrated the relationship between SSTL and objective accident numbers, but research on the broader implications of SSTL for organizations and organizational performance is lacking. We aim to contribute to the literature by studying SSTL in 87 warehouses in the Netherlands, surveying 87 warehouse managers and 1,233 warehouse employees to address the two questions outlined above: What are the antecedents of SSTL, and to what extent does SSTL impact operational performance in terms of quality and productivity?

5.2 Theory

Occupational accidents

Employees worldwide are at risk of becoming involved in occupational accidents that can have a serious impact on employees, companies and society as a whole. The situation in the Netherlands is not different. Even though the estimated fatality rate in the Netherlands is relatively low (1.5 fatalities per 100,000 workers; Hämäläinen et al., 2009), about 458,000 employees were involved in an occupational accident resulting in physical or mental injury in 2013 (CBS, 2014). This is approximately one in fifteen employees. For nearly half of the employees involved in an occupational accident, the accident resulted in at least a one day absence. The financial, reputational and legal consequences of these accidents and the resulting employee absence are severe, and it is therefore not surprising that companies have a great interest in gaining insight into how these accident numbers can be reduced. Warehouses, often characterized by a mix of vehicle and pedestrian traffic streams, form the backdrop of many occupational accidents. For example, a study by the U.S. Bureau of Labor Statistics (Bureau of Labor Statistics, 2012) showed that approximately 4.5% of all full-time warehouse workers in the U.S. had experienced an injury. This percentage is substantially higher than the percentage in other industries that are known to be risky, such as logging (3.4%), mining (3.2%) and construction (3.1%) (Bureau of Labor Statistics, 2012). Not surprisingly, a substantial number of the risk factors of occupational accidents that have been identified by the Netherlands Organization for Applied Scientific Research TNO (2012) apply to warehouses. The workforce in warehouses is often characterized by a high turnover (Min, 2007), they face irregular working hours (McMenamin et al., 2007), and have to cope with fluctuating work volumes, leading to substantial pressure (De Koster et al., 2011). The impact of reducing occupational accidents by only a small percentage might be substantial, as this small percentage could mean the prevention of many fatalities. Thus, research on warehouse safety is highly important.

A large number of studies and theories has focused on the technical aspect of safety systems and procedures. Examples are Perrow’s Normal Accident Theory (1984), stating that accidents are inevitable in tightly coupled systems with sufficiently complex technologies, and High Reliability Organizational Theory (LaPorte and Consolini, 1991), stating that accidents can be avoided in complex highly reliable organizations. However, especially during the last decade, the scope has gradually shifted to an increased interest in how the management and other “softer” organizational factors impact workplace safety (DeJoy et al., 2004). Hale and Hovden (1998) have referred to this shift towards a more behavioral view on occupational safety as ‘The Third Age of Safety’. In the ‘Third Age of Safety’, behavioral constructs such as safety culture (a sub-component of corporate culture that encompasses safety-related features at job, employee, and organizational levels; Cooper 2000), safety climate (the perception of employees on an organizational level about how relevant and important a safe way of working is for their daily occupation; Zohar 1980), and safety consciousness (awareness and a positive attitude toward acting safely on an individual level; Forcier et al., 2001) have entered the safety research domain.

These behavioral constructs emphasize the importance of perceptions of employees and the organization as a whole regarding the relevance of safety on the work floor (Glendon and Stanton, 2000). Also, considering the prominent role of leaders in shaping employee perception and sense making (cf. Shamir et al., 1993), this highlights the importance of managers and leaders in fostering safety. Some studies describe the influence of management decision making and system implementation on occupational safety (LaPorte, 1996), and research by Barling et al. (2002) and Zohar (2000; 2002) has helped the field develop by including leader behavior toward subordinates as a factor that influences the level of safety concern of subordinates. The model of safety-specific transformational leadership developed by Barling et al. (2002) has illustrated that managerial behavior can indeed have a substantial influence on the safety perception and behavior of employees, and on the actual number of occupational accidents (De Koster et al., 2011).

Safety-specific transformational leadership (SSTL)

Transformational leadership is a type of leadership that leaders use to encourage employees to prioritize the mission of the team or organization over personal goals (Bass, 1990, 1985). A substantial body of research on transformational leadership exists, linking the concept to employee motivation (Masi and Cooke, 2000; Shamir et al., 1993), innovative performance (Deichmann and Stam, 2015; Howell and Avolio, 1993; Nederveen Pieterse et al., 2010), and follower and organizational performance (Dvir et al., 2002).

Barling et al. (2002) developed a construct named “safety-specific transformational leadership” (SSTL). SSTL can be defined as a form of transformational leadership focused on achieving safety outcomes. Adapting the regular construct of transformational leadership to meet the specific requirements of a safety context is essential, since safety is often a company outcome that is not directly a core part of the company vision. Some company outcomes might even be at odds with safety as an operational target. However, occupational accidents are detrimental for every company, and investigating SSTL helps us to discover how transformational leadership can be used to reduce such accidents. Transformational leadership is believed to be comprised of four factors (the four I's), which also apply to SSTL: idealized influence, inspirational motivation, intellectual stimulation and individualized consideration (Avolio et al., 1991). In the context of safety, these four factors respectively refer to acting as a role model with regards to safety, communicating a vision in which safety plays an essential role, encouraging employees to think about how they can work more safely, and being actively involved with the safety of individual employees. The combination of these four factors should lead to higher occupational safety performance. In addition to these factors, contingent reward is also part of Barling et al.'s (2002) SSTL scale. Even though contingent reward is originally a part of the transactional leadership scale (Bass and Avolio, 1990), it has consistently been linked to transformational leadership (Goodwin et al., 2001). Transformational leaders are thought to effectively get followers on board with their vision by motivating them with contingent rewards, after which intrinsic motivation should take over (Goodwin et al., 2001).

The relationship between SSTL and occupational safety has been investigated in multiple studies. Barling et al. (2002) found that SSTL related to self-reports of occupational injuries in the food and beverage industry (Study 1), and in high schools, colleges and community centers (Study 2). Kelloway et al. (2006) found a similar relationship using self-reports of college students. Relevant for the current study, De Koster et al. (2011) authored the first study to demonstrate that SSTL relates to objective accident rates in warehouses, even when controlling for a wide variety of hazard-reducing systems. Based upon our review of the relevant literature, discovering the antecedents and outcomes of SSTL other than safety is critical to research and practice.

What are the antecedents of SSTL? The role of prevention focus.

Although no prior research has investigated the antecedents of SSTL directly, prior research by Judge and Bono (2000) has employed the big-five factor structure of personality (Goldberg, 1990) as a predictor of more general transformational and transactional leadership behaviors. Even though the results of this study suggested that extraversion and agreeableness positively relate to transformational leadership, a subsequent meta-analysis showed only very weak evidence for the dispositional basis of transformational leadership (Bono and Judge, 2004). Bono and Judge, therefore, stressed the necessity of research on transformational leadership that employs more specific personality traits or antecedents like motivations or motivational strategies (2004).

We argue that the concept of regulatory focus can help to better understand SSTL. Higgins' regulatory focus theory (Higgins, 1987, 1996, 1997) states that there are two separate and independent self-regulatory strategies that play an important role in guiding behavior. The basic principal behind these two strategies is the fundament upon which many psychological theories are built and can be employed to discuss almost any area of motivation (Higgins, 1998). The first strategy, a promotion focus, is an inclination towards reaching a desired positive and attractive end-state. People displaying a promotion focus are eager to achieve, will emphasize ideals and focus on advancement. They are focused on the attributes that they would ideally wish or aspire to possess. The other strategy, a prevention focus, is aimed at reaching an end-state because of a fear of the alternative. It focuses on the attributes that people should or ought to possess, their duties, obligations and responsibilities. People displaying a prevention focus are vigilant and careful not to lose; they will emphasize fears and want to avoid these fears (Higgins, 1997).

In the context of occupational safety and SSTL, we expect that especially a prevention focus plays a vital role. It has been consistently linked to prioritizing safety and security (Crowe and Higgins, 1997; Higgins, 1998), to the avoidance of mistakes and errors (Higgins, 1997), and to conscientiously following rules and regulations (Wallace, Johnson, and Frazier, 2009). For example, Crowe and Higgins (1997) demonstrated in an experiment with a signal detection task that people with a strong prevention focus responded more conservatively and generally took more time to respond to ensure their answers were correct. Furthermore, Friedman (1999) stated that people with a strong prevention focus firmly believe that all of their actions are required to achieve the goal they want to achieve. A safe working environment is the consequence of a combination of many actions and measures. Therefore, a prevention focus is expected to have a strong positive effect on occupational safety. Werth and Förster (2007) give an example of the relationship between prevention focus and safety in a different context. They found that when spontaneous braking was required in ambiguous traffic situations, promotion-oriented individuals were braking much later than prevention-focused people. Gorman et al. (2012) and Lanaj et al. (2012) pointed out in their meta-analyses that in work contexts where safety is crucial, a prevention focus is preferred because people with such a focus prioritize avoiding injury over achieving maximal performance on the job. Still, Gorman et al. (2012) also called for additional research to explore the influence of a prevention focus in the context of safety. Linking regulatory focus in this context of safety with the influence of leadership, Kark and Van Dijk (2007) posited that a leader's regulatory focus influences his or her values and leadership style. For example, a leader's prevention focus is expected to positively relate to values of conservation such as safety and tradition. This will, in turn, result in a leadership style with an emphasis on duties and responsibilities (Kark and Van Dijk, 2007), such as SSTL. This leads to the following hypothesis:

H1a**:** *Prevention focus of warehouse managers positively relates to safety-specific transformational leadership (SSTL) of warehouse managers.*

This expected positive relationship between a prevention focus and SSTL of warehouse managers can be combined with the negative relationship between SSTL of warehouse managers and warehouse accidents identified by De Koster et al. (2011). We believe that this relationship is part of a larger model in which a prevention focus of the manager manifests itself as a safety-oriented leadership style, which then relates to lower accident rates. This expectation about the mediating role of SSTLis reflected in hypothesis 1b:

H1b**:** *SSTL of warehouse managers mediates the negative relationship between prevention focus of warehouse managers and warehouse accidents.*

To what extent does SSTL affect operational performance?

Productivity. For companies it is much easier to assign a monetary value to productivity than to safety (Starr and Whipple, 1984). Still, it is essential for companies to find out how to combine working safely with working productively. Transformational leadership has frequently been linked to higher performance effectiveness and performance of followers (e.g. Howell and Avolio, 1993; Lowe et al., 1996). SSTL emphasizes different aspects of performance. Through SSTL, managers aim to shift the focus of employees towards occupational safety instead of productivity results. Managers leading through SSTL spend time on demonstrating how safety can be improved at the workplace, convincing employees of the importance of safety, emphasizing that every employee can make a difference in preventing accidents, and inspiring them to take initiatives regarding safety (Barling et al., 2002). As a result, employees will take less risk, take extra care to avoid errors, and double check procedures and activities. For example, a forklift driver could decide to drive substantially slower because he is always aware that accidents may happen unexpectedly. The resulting loss in productivity could be potentially compensated on the longer term by a reduction in accidents. However, the direct relationship between SSTL and productivity is expected to be negative. This leads to the following hypothesis:

H2: *SSTL of warehouse managers negatively relates to warehouse productivity.*

Quality. For many companies, the quality of their products, services and workflows is a top priority. Especially since the 1990s, companies have focused on improving business processes through the diffusion of Total Quality Management within the total organization (Tanninen et al., 2008). The quality-related aims of a company (avoiding errors, defects and customer complaints) generally correspond well with the main objective of SSTL: fostering safety in the workplace. Even though the occurrence of defects in a warehouse might not be directly linkable to safety (e.g., a ‘mispick’ does not have catastrophic safety consequences), SSTL and quality are expected to be closely related in this context. By influencing, inspiring, stimulating, and individually considering employees with respect to safety (Barling et al., 2002), managers leading through SSTL emphasize to their employees that even the smallest actions they undertake at their job can influence occupational safety. Focusing work details, double checking procedures and working carefully and vigilantly are expected to also positively influence the general accuracy of employees. They become aware that working with high precision leads to desirable outcomes. Consequently, we expect that a higher level of SSTL of the manager relates to a decrease in the number of quality defects (such as errors and complaints), which is stated in the following hypothesis:

H3: *SSTL of warehouse managers positively relates to process quality of the warehouse.*

All hypotheses are summarized in Figure 7, which displays the conceptual model.

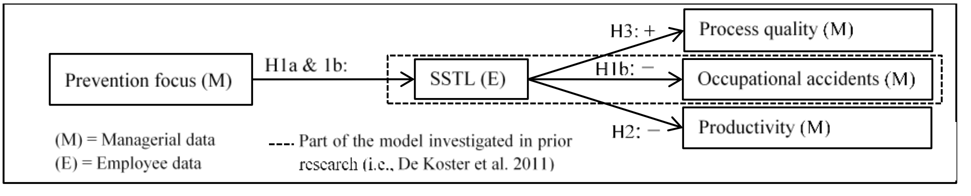

Figure 7: Conceptual model

5.3 Methodology

We investigated the hypotheses using data obtained through surveys filled out by 1,233 warehouse employees and the managers of 87 warehouses, leading to an average of 14 employees (standard deviation = 5.55) and 1 manager per warehouse. The minimum number of employees participating per warehouse was 5. The 87 warehouses in the sample represent a variety of (in total 11) industries, such as Food and Beverages (13.8%), Automotive (11.5%), Computer and Electronics (8.0%), and various others. Small warehouses (< 40

FTEs: 44.8%), medium-sized (40-100 FTEs: 28.8%) and large warehouses (> 100FTEs: 26.4%) were represented.

For 55 warehouses, the data used to test the proposed relationships partly overlap with the data employed by De Koster et al. (2011), who investigated the influence of safety-specific transformational leadership, hazard reducing systems and safety consciousness on occupational accidents among 78 warehouse managers and 1,033 warehouse employees. Fifty-five of the original 78 warehouses (71%) agreed to take part again and provided additional information on recent accidents, prevention focus, productivity, and process quality. T-tests did not reveal significant differences in the mean scores of SSTL, occupational accidents, and the four different hazard reducing systems between the 55 participating warehouses and the 23 warehouses not participating in the current study. Furthermore, 32 new companies were added to the sample, leading to a total number of 87 participating companies. These new companies were recruited by approaching 410 warehouses that were randomly selected from a database of a Dutch industry association of material handling suppliers (BMWT). Chemical companies were not approached, as the higher risks associated with this industry typically lead to extremely stringent safety rules and regulations that dominate all warehouse processes. Of the 410 newly approached companies, 61 (14.9%) could not be reached due to an incorrect or nonexistent e-mail address of the manager, and 281 companies (68.5%) did not respond at all. No overrepresented sector could be identified among the non-respondents. Of the remaining 68 companies, 36 (8.8% of the total) replied negatively to the participation request, usually because of a lack of time or a shift in priorities within the warehouse. Thirty-four (8.3% of the total) companies responded positively to the participation request. We excluded two companies; one because it employed fewer than 5 warehouse employees, the other because it only employed people with a handicap. The managers and employees in all 32 remaining companies completed the extended questionnaires.

To every warehouse that indicated willingness to participate we sent 20 paper and pencil questionnaires for warehouse employees, including preaddressed envelopes to ensure full anonymity. Managers were instructed to select a representative sample of employees in different positions to fill out the survey. The managerial survey was sent and returned digitally through e-mail. The percentage of participating employees per warehouse varied from 3.2% (19 out of 600 employees participated) to 89% (18 out of 20 employees participated). In total, 85.6% of the workers were male, 32.9% were aged between 15 and 34 (34-42: 22.9%, 43-66: 44.2%), 79.9% worked on a fixed contract basis (20.1% had a flexible or temporary contract, 85.4% worked full-time), and 88.9% had worked for the warehouse for more than a year (52% for more than 4 years). High school was the highest level of completed education for 40.5% of the employees, and only 9.8% of the employees completed at least a polytechnic or university education. Of the managers, 97.8% were male, 32.6% were between 25 and 41 years of age, (41-49: 35.9%, 50-61: 31.5%), and all of them had worked for the warehouse for more than a year (91.4% for more than 4 years). Even though the sample contains warehouses from various sectors and sizes, it should be considered that safer warehouses were more likely to participate than unsafe warehouses. Although we ensured confidentiality, companies are hesitant to share this type of information because of the reputational damage it might cause. Since most unsafe warehouses are not likely to be included in the sample, and since occupational accidents in the Netherlands are relatively rare, our sample is biased towards safer warehouses. This bias makes it more difficult to discover statistically significant relationships, since the total number of accidents that occurred in the investigated warehouses is relatively low. We therefore think that the insights obtained in this challenging research context should definitely generalize to warehouses with relatively more accidents, a context in which the impact of the findings could be larger as well.

Variable operationalization

Occupational accidents (manager questionnaire). We measured the number of accidents for each warehouse over the period 2006-2010. We added 1.5 years (2009-2010) to the original period investigated by De Koster et al. (2011) and removed the first year (2006) to ensure we had sufficient data, while excluding old data that might not be connected to the current safety policy of the warehouse. Most of the participating managers (91.4%) had worked in their warehouse for at least 4 years. For the 8.6% of the managers who had worked in the warehouse for 1-3 years, we took only the latest year of accident data into account. The year 2010 was the most recent full year for which accident data was available at the time of the survey. We divided the score by the number of full-time equivalents (FTEs) because in absolute terms more person-related accidents are expected to happen in facilities with more employees. Also, we divided the score by the number of years that were taken into account for each individual warehouse to end up with a measure of the number of accidents per FTE per year. Following the method of the Netherlands Research Institute TNO, we measured the following categories of occupational accidents:

1. Occupational accidents resulting in injury, but not leading to absence.
2. Occupational accidents resulting in injury and a minimum absence of one day.
3. Occupational accidents resulting in hospital admission after a visit to the hospital emergency department.
4. Fatal occupational accidents.

For 55 warehouses, three years of accident data overlap with the study by De Koster et al. (2011). For the other 32 companies all collected data is new. To ensure that the findings of this study cannot merely be attributed to the data that was also used in the previous study, we examined the correlation between SSTL and the occupational accidents score only for the 32 new companies. Like in the previous study, this correlation is negative ($r = -.365$). This indicates that the newly added companies reinforce the previous important finding that SSTL relates to a lower level of occupational accidents. Subsequently, we compared the accident data from the overlapping years with the newly gathered 1.5 years of accident data. This was only done for the first and second accident categories, because they contained enough accidents (957 and 581 respectively) to reliably test for this, whereas the more severe third and fourth categories did not contain enough accidents (61 and 1 respectively) to facilitate a comparison. The correlation in accident scores was substantial ($\bar{R}$ = .563, range: .267-.908) and significant ($p < .05$) across all years, suggesting that the data consist of stable patterns rather than just a small number of outliers in particular years. Furthermore, since the accuracy of this study greatly depends on the accuracy of the accident data provided by the manager, we compared the accident data to official accident data obtained through the Inspectorate SZW (Dutch Labor Inspectorate of the Ministry of Social Affairs and Employment). Companies are required to report their severe accidents to this inspectorate. These data are highly confidential, and the Inspectorate could only provide data for companies participating in our study that had already reported their accidents. Even though a comparison was only indirectly possible because the Inspectorate employs slightly different accident categories and does not register very minor accidents, comparing their data with the data obtained through the managerial surveys showed that the patterns in the two datasets were similar per warehouse.

In the analyses, we employed the accident scores as indicators of a latent variable in the PLS-SEM model. We also took the average of the z-scores per category over the four categories to arrive at a weighted measure of accidents to check for the robustness of the results.

Safety-specific transformational leadership (SSTL) (employee questionnaire). We used Barling et al.'s (2002) 10-item scale to measure the manager's SSTL. Employees used a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) to rate their manager on various sub-dimensions of SSTL: idealized influence, inspirational motivation, intellectual stimulation, individual consideration, and contingent reward. The scale is based on the Multifactor Leadership Questionnaire (MLQ) by Bass and Avolio (1990), which was originally constructed to measure general transformational leadership. Investigating the reliability of the complete SSTL scale per warehouse using SPSS revealed a sufficiently high Cronbach's alpha of .993 (reliability measures for the first order constructs ranged from .697 to .988). Furthermore, following the steps explained by Bliese (2009) we used the multilevel package in R 3.0.1 (R Core Team, 2013) to find out if aggregation of the SSTL data to warehouse level was appropriate. The obtained ICC(1) value of .25 indicates that 25% of the variance in individual SSTL ratings can be explained by the warehouse level, and the obtained ICC(2) value of .82 indicates that warehouses can be reliably differentiated in terms of average SSTL scores (Bliese, 2000). Therefore, we took the average of all employees of a particular warehouse to obtain a single score per item per warehouse. Subsequently, the items were grouped to obtain the SSTL scores of the warehouse manager on the five-subdimensions. For the 55 warehouses of which three years of accident data overlap with De Koster et al. (2011), the SSTL data also overlap with the data employed in this study.

Prevention focus (manager questionnaire). We used the regulatory focus at work scale (RWS) by Wallace and Chen (2006) to measure the prevention focus of the manager. The validity and internal consistency of this scale has been determined by various case studies in work contexts (Wallace et al., 2009). We translated the questionnaire to Dutch to accommodate the participating managers. They were also back-translated to English to ensure accuracy of the translation. The prevention focus scale consists of 6 work-related statements ($\alpha = .855$).

Warehouse productivity (manager questionnaire). We measured the efficiency of the warehouses using data envelopment analysis (DEA), which can relate multiple inputs to multiple outputs. The DEA method seems appropriate in the case of warehouses, since it is possible to take a set of variables that jointly define the productivity in the warehouse. The outcome of DEA is a single score that can be interpreted as the efficiency score of a warehouse. Even though various different output measures could be used, De Koster and

Balk (2008) already mentioned that these output indicators are usually closely related to each other and depend on the similar sets of input factors (e.g., surface of warehouse, degree of automation, etc.). The DEA score is composed of the following input factors:

1. The average number of stock keeping units (SKU) stored in the warehouse in 2010.
2. The surface of the warehouse in square meters.
3. The number of direct and indirect full-time equivalents (FTEs) of the warehouse.
4. The degree of automation and use of information systems in the warehouse. We used the same measurement as De Koster and Balk (2008), who employed a five-point scale with a higher score for warehouses using more advanced WMS systems, radio-frequency technology, and robots, etc. We standardized this score before use in the analyses.

We used the number of order lines picked as output factor in the DEA analysis. An assumption of DEA is that the output factor should correlate (positively) with at least one input factor (Dyson et al., 2001). Of the four inputs, the number of FTEs correlated significantly with the output factor.

We used Efficiency Measurement System software (EMS version 1.3) to calculate the DEA scores ($\bar{x}$: 48.65%, s: 27.9%). Following Charnes, Cooper and Rhodes (1978), Constant Returns to Scale (CRS) were assumed in the calculation. To distinguish the 100% efficiently rated warehouses in this analysis, we also calculated super-efficiency (> 100%; Zhu, 2001). These super-efficiency scores ($\bar{x}$: 74.4%, s: 54.2%) were standardized before being used in subsequent analyses.

Quality (manager questionnaire). We measured the quality performance of each warehouse by the average percentage of order lines sent without errors (i.e., mispick, mislabel, etc.) during the past year, as reported by the manager. We also asked the manager to report the percentage of orders sent without complaints. Most companies reported the same percentage of orders sent without complaints as the percentage of order lines sent without errors. Therefore, we used only this percentage in the subsequent analyses. Before being used in the analyses, we standardized the percentage of order lines sent without errors and treated it as continuous variable.

Control variables. Hazard reducing systems (HRS) (manager questionnaire) were represented by four factors (Traffic, Training, Hygiene, and Storage) that jointly capture approximately half of the variance in hazard reducing systems. These factors were measured using 26 items, following the research by the De Koster et al. (2011). Age and education of the manager were also used as control variables. Safety consciousness of the employees is not included in this study because it builds upon the results of De Koster et al. (2011), who did not identify a substantial role of safety consciousness in this context.

5.4 Analyses and results

As a starting point, we used a one-way ANOVA to test for differences in the dependent variables between the 11 sectors. No significant differences in accidents (F (10, 76) = .899, p = .538), productivity F (10, 75) = .515, p = .875) or quality F (10, 67) = .548, p = .850) were found. Tukey post-hoc comparisons of the 11 sectors did not reveal any differences in the dependent variables between pairs of sectors. In terms of productivity, the absence of differences between sectors might seem surprising. However, this finding can largely be explained by the large within-sector variance in productivity, in addition to potential between-sector variance. For example, a warehouse in the automotive sector could involve the picking of small items such as screws and lightbulbs, but another warehouse in the same sector might mainly handle larger items such as complete engines or wheels. Since no differences between the sectors were identified, we did not control for sector in the remainder of the analyses. Table 26 displays the correlations between the (standardized) variables that were used in the subsequent analyses. No significant tradeoffs between the number of accidents, productivity, and quality can be observed.

Table 26: Correlation table

Variable	1	2	3	4	5	6	7
1 Category 1 accidents							
2 Category 2 accidents	.396**						
3 Quality	.021	-.124					
4 Productivity (DEA)	.019	-.061	.059				
5 SSTL	-.311**	-.294**	-.087	-.092	*.933*		
6 RF: Prevention	-.235*	-.159	-.074	.014	.542**		
7 Age Manager	.228*	.253*	.191	.034	-.138	-.142	
8 Education Manager	.039	-.146	.227*	.077	.037	-.125	-.136

Note: $N = 87$. Pairwise deletion of missing values employed, resulting in a lower N for some correlations.
* $p < .05$, ** $p < .01$. Cronbach's α is displayed in italics on the diagonal of the relevant variables.

We employed partial least squares structural equation modeling (PLS-SEM) using SmartPLS (Ringle et al., 2005) to investigate our hypotheses through structural equation modeling. We chose partial least squares structural equation modeling instead of covariance-based SEM because it fits better with the non-normal distributions of some of our data and relatively small sample size (Hair Jr et al., 2013). To facilitate significance testing of the obtained parameter estimates, we employed a bootstrapping procedure which makes use of 5000 subsamples generated from the original dataset. A significance level of .05 is used with this procedure.

Measurement validation

The initial model included all accident categories as indicators of the latent variable representing accidents. However, due to the relatively low number of observations of the two most severe accident categories (cat. 3 and 4), the validity and composite reliability of this latent variable was not meeting the commonly employed thresholds. Because of this, the final model only employed accidents in categories 1 and 2 as indicators.

Validity: The cross loadings reveal that all indicators load significantly on the appropriate constructs without excessive cross-loadings on other constructs. Also, the square root of the average variance extracted (AVE) of every construct is higher than its correlation with any other construct, providing evidence for discriminant validity. The AVE of SSTL

(.89), prevention focus (.58), and accidents (.70) meet the threshold of .50, providing evidence for convergent validity.

Table 27: Descriptive statistics and factor loadings of variables and items

Construct	Composite reliability	AVE	Item	Mean	SD	Standardized path loading	T-statistic
Accident score	0.822	0.7	Category 1 accidents	0.028	0.029	0.85	5.14
			Category 2 accidents	0.015	0.018	0.82	5.53
Quality	-	-		0	1	-	-
Productivity (DEA)	-	-		0	1	-	-
SSTL	0.98	0.89	CR: Contingent Rewards	4	0.82	0.86	17.04**
			IC: Individualized Consideration	4.18	0.72	0.96	109.95**
			II: Idealized Influence	4.03	0.97	0.95	77.75**
			IM: Inspirational Motivation	4.25	0.82	0.98	147.42**
			IS: Intellectual Stimulation	4.09	0.79	0.98	188.31**
Prevention Focus	0.89	0.58	1. Following rules	3.8	0.66	0.76	12.25**
			2. Tasks	3.89	0.6	0.78	12.57**
			3. Duty	3.76	0.65	0.8	13.50**
			4. Responsibilities	3.69	0.61	0.79	17.34**
			5. Obligations	3.58	0.61	0.83	18.01**
			6. Details	3.12	0.62	0.56	3.95**
Age Manager	-	-		43.86	9.08	-	-
Education Manager	-	-		3.86	0.78	-	-

* $p < .05$, ** $p < .01$

Reliability: The composite reliability of SSTL (.977) prevention focus (.889), and accidents (.822) are higher than the commonly prescribed threshold of .70. All indicators of SSTL and accidents also load higher on the factor than the commonly prescribed threshold for indicator reliability of .708, demonstrating that the individual indicators are reliable (Hair Jr et al., 2013). The same applies to the items of prevention focus, with the exception of indicator 6. However, the loading of .56 is not expected to be problematic as long as the AVE of the scale meets the threshold of .50 (Hair Jr et al., 2013). Table 27 displays the descriptive statistics and factor loadings of the items used in the final PLS model.

Structural model

Figure 8 displays the structural model and the associated path coefficients. This model significantly explains 31.1% of the variance in SSTL, and 13.1% of the variance in the accident scores. The effect size f^2 of prevention focus on SSTL is 0.38, indicating a large effect (Hair Jr et al., 2013). A blindfolding procedure as described by (Hair Jr et al., 2013) with omission distance of 7 revealed positive Q2 values for SSTL of .25 and for accidents of .06, pointing out that the model has predictive relevance. The results supports Hypothesis 1a by demonstrating that a prevention focus of the manager positively relates to the manager's safety-specific transformational leadership (β = .551; p < .01). To test the mediating role of SSTL (Hypothesis 1b), we performed a mediation analysis following the procedure proposed by Zhao et al. (2010). We performed a bootstrap test to assess the indirect effect of prevention focus on the accident score with SSTL as mediator. This yields a significant indirect effect of prevention focus on the accident score (β = −.199; p = .02) indicating mediation is taking place and supporting Hypothesis 1b. The full model shows no significant relationships between SSTL and both productivity (β = −.092; p = .39) and quality (β = −.084; p = .425), contrary to Hypotheses 2 and 3.

These results suggest that a manager with a higher prevention focus is more likely to display SSTL, which in turn relates to a lower number of accidents. This relationship is not accompanied by a positive or negative relationship between SSTL and the other important warehouse parameters productivity and quality.

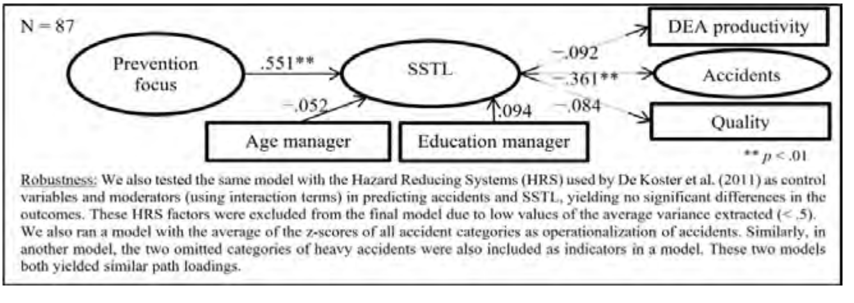

Figure 8: PLS structural model

To quantify the effect of prevention focus on safety, we compared the number of accidents per FTE per year between the twenty companies with the most strongly prevention-focused managers and the twenty companies with managers scoring relatively low on prevention focus, while controlling for the various Hazard Reducing Systems, age, and education of the manager. On average, there were twice as many occupational accidents in the companies with managers scoring relatively low on prevention focus than in the companies with the most strongly prevention-focused managers (Table 28).

Table 28: Comparison between top 20 and bottom 20 prevention-focused Managers

	Top 20 prevention-focused managers		Bottom 20 prevention-focused managers		Ancova test statistics
	Mean	*SD*	*Mean*	*SD*	F
Prevention Focus	4.82	0.21	3.13	0.44	
Accidents/FTE per year	0.034	0.027	0.066	0.051	4.52*
SSTL	3.97	0.41	3.15	0.7	7.48*

5.5 Discussion and conclusion

The frequent occurrence and severe consequences of occupational accidents highlight the need for more research on how these accidents can be prevented. Barling et al. (2002) have enriched the literature on occupational safety by emphasizing the vital role of leadership and by introducing the concept of SSTL. This construct has been linked to various safety-related outcomes such as safety climate, safety consciousness (Kelloway et al., 2006), and occupational accidents (De Koster et al., 2011). Even though the important role of leadership, and specifically SSTL, in fostering occupational safety has been demonstrated, there are still various key issues that need to be investigated. This study contributes to prior research on SSTL by addressing some of these issues.

First, this study is one of the first to examine an antecedent of SSTL. The results suggest that a manager's prevention focus positively relates to SSTL as a leadership style, and through SSTL, to a lower number of warehouse accidents. This contribution is not only of theoretical importance, but also relevant in practice, in view of the severe consequences of occupational accidents. Second, this study does not only replicate existing literature by investigating the influence of SSTL on safety-related outcomes, but also shows its relation with other important warehouse performance indicators such as productivity and quality. The results suggest that SSTL's positive relationship with safety does not co-occur with a positive or negative relationship with quality or productivity. This result differentiates SSTL from transformational leadership, which has commonly been linked to increased organizational performance and commitment to quality (e.g. Dvir et al., 2002; Masi and Cooke, 2000).

Implications

Implications for researchers. In this study we identified that a manager's prevention focus strongly relates to SSTL and, through SSTL, to a lower number of warehouse accidents (Hypotheses 1a and 1b). This is an important extension of the models proposed by Barling et al. (2002) and De Koster et al. (2011), and is a vital finding that should be considered in the future development of more comprehensive models incorporating SSTL and transformational leadership. The research on transformational leadership has traditionally emphasized the outcomes of this leadership style more than its antecedents. Knowledge on the dispositional or situational antecedents is essential for companies in need of transformational leadership, as it could enable the prediction of which leaders will display transformational leadership after being hired (Barbuto and Burbach, 2006). Personality (e.g. Howard and Bray, 1988), personal attributes, and motivation (Barbuto Jr. et al., 2000) are some rare examples of potential antecedents of transformational leadership that have been identified. Also regulatory focus, known as construct that plays a central role in shaping people's motivation and behavior (Higgins, 1998, 1997) has been conceptually linked to transformational leadership, but empirical evidence of this relationship is still lacking (Kark and Van Dijk, 2007). By empirically demonstrating that a prevention focus relates to a safety-specific transformational leadership style, this study helps to address this issue

Similar to previous research (Barling et al., 2002; De Koster et al., 2011; Kelloway et al., 2006), this study also found a strong relationship between SSTL and safety. However, even though this strong relationship has been confirmed, we acknowledge there is a limit to the difference that behavioral aspects can make in an operational environment. In doing so, it is important to realize that the shift towards the behaviorally oriented ‘Third Age of Safety’ (Hale and Hovden, 1998) does not mean that the more technical perspectives have been completely replaced. Rather, it implies that safety research should consider additional factors to complement existing views.

We also investigated the relationship of SSTL with other operational outcomes, but evidence for the expected negative relationship between SSTL and productivity (Hypothesis 2) or positive relationship between SSTL and quality (Hypothesis 3) were not found. This is remarkable, since research has consistently linked the transformational leadership construct to positive outcomes such as increased performance (Dvir et al., 2002; Howell and Avolio, 1993; Masi and Cooke, 2000) and commitment to quality (Masi and Cooke, 2000). However, the fact that we found neither a negative nor a positive relationship between SSTL and productivity implies that a focus on safety is not necessarily detrimental for productivity. Further research is required to investigate the causes and boundary conditions of this finding before solid conclusions can be drawn.

This finding suggests that it is not possible to simply generalize the identified effects of transformational leadership across different contexts. In particular, more specific transformational leadership constructs can be valuable for contexts in which specific outcome variables, such as safety performance, are evaluated. The same could apply to situations in which other specific outcomes, such as innovation or learning performance play a vital role. In this way, the development and use of more context-specific transformational leadership constructs does not lead to a fragmentation, but rather to a broadening of the research on transformational leadership.

In addition, future research should aim to connect the findings of the current study with several existing studies. For example Kark and Van Dijk (2007) linked the regulatory focus of leaders to the regulatory focus of followers, and Wallace and Chen (2006) demonstrated the link between prevention focus of employees and safety performance. Based on a combination of these results, it would be highly interesting to find out whether SSTL of the manager relates to safety performance through employee prevention focus. Moreover, we know very little about the long-term effects of a manager's safety leadership on factors such as employee well-being, turnover, and organizational commitment. Incorporating these aspects in future models will provide a more complete image of the impact of a manager's safety focus on employees.

Implications for managers. In this study, we found that a dispositional prevention focus of the manager relates to SSTL, which in turn relates to a lower number of accidents. We did not find evidence that these benefits are attained at the expense of quality or productivity in the warehouse. This finding is relevant to managers, since the common assumption in research and practice is that a focus on safety trades off with speed/productivity (Zohar and Luria, 2005), and that safety and quality go hand in hand because they rely on the same type of measures that reduce variability in production processes (García Herrero et al., 2002). Especially the identified absence of a negative impact on productivity of SSTL could remove an obstacle for managers aiming to increase the emphasis on safety in their organization through their leadership, resulting in a rise in financial returns because of fewer accident-related expenses. Companies frequently invest substantial amounts of money in safety improvement, but often underestimate the effect of leadership on occupational safety. These companies are likely to benefit from a manager who displays SSTL. Therefore, the aim of such companies should be to find out whether their manager leads in a way that is consistent with SSTL.

Furthermore, the positive relationship between SSTL and safety stresses that safety-focused leadership should become a part of most leadership development programs.

Such programs commonly focus on the importance of transformational leadership, but constructs such as SSTL are usually neglected despite the obvious need for safety-oriented managers in many companies. Similarly, in selection and assessment procedures, SSTL should become one of the criteria used to select suitable candidates for managerial positions. However, before hiring a manager it is difficult to assess his or her specific leadership style, and it is probably only possible to find out whether a manager displays SSTL at a later stage. However, it is relatively easy to measure whether a potential manager is prevention-focused during an assessment procedure, which can provide companies with insight into the likelihood that this person will become a safety-specific transformational leader positively contributing to occupational safety.

Strengths and limitations

This research can be characterized by several strengths and limitations. One of the positive aspects is that the study makes use of data obtained through both employees and managers to test the hypotheses, and that the accident data have been verified with an external data source. Similar to the approach of De Koster et al. (2011), our approach is less susceptible to common-method bias than most research in this field that mainly uses employee perceptions. However, ideally this research should make use of time series data to establish causality. Even though the large majority of the managers had been at working at their position for at least four years, the direction of causality cannot be firmly established using this method. Unfortunately, the possibility still exists that the safety policy of previous managers accounts for the current number of accidents.

Also, even though the linkage of SSTL to non-safety-related outcomes such as quality and productivity can be considered novel, we did not identify any influence of SSTL on these outcomes. A possible explanation for this could be the way in which the variables were operationalized. For example, even though DEA is a widely accepted method to compare companies in terms of productivity (Emrouznejad et al., 2008), there might also be other factors that influence warehouse productivity outside the scope of our DEA measurements.

The use of additional productivity operationalizations and control variables (e.g. the number of forklifts in the warehouse) in future studies would therefore be desirable to find out whether a correlation between SSTL and productivity or quality does not exist, or whether we have not been able to discover it because of our operationalizations.

Furthermore, the participating warehouses are active in a variety of sectors, contributing to the generalizability of the results. However, the surveyed warehouses are likely to operate more safely than the average Dutch warehouse. Informally asking some warehouses not willing to participate for their underlying motivation suggests that a considerable share of the non-responding warehouses (about 92% of all approached warehouses) did not reply because they were afraid to share this information, or because they might suffer from relatively high numbers of occupational accidents. This non-response is problematic, because the effects of SSTL should be especially visible in these warehouses. Potentially parts of this study could be replicated in countries with a public accident registration system that also includes minor accidents, which would remove some of the barriers to participation.

In a sample of 87 warehouse managers and 1,233 warehouse employees, this study investigated the antecedents of SSTL and the non-safety-related outcomes of SSTL. This study only includes data from warehouses in the Netherlands, but many of these ship internationally or are run by multinational companies. We therefore believe that this sample is sufficiently representative to draw conclusions for medium and large warehouses in Western Europe. The results extend the established finding that SSTL is important in fostering occupational safety into a more comprehensive model. In this model, a manager's prevention focus antecedes his or her SSTL. Also, we did not identify a relationship with productivity or quality in the warehouse. This study not only contributes to the under-researched field of occupational safety and especially the role of leadership in this matter, but also aims to make a difference for some of the vast number of employees who become victims of occupational accidents every day.

Chapter 6

Which Drivers Should Transport Your Cargo? Empirical Evidence from Long-Haul Transport

6.1 Introduction

Road safety is a prime concern for drivers and public policy makers worldwide. Especially professional drivers, commonly driving for long monotonous periods and in irregular shifts, are exposed to a relatively high risk of encountering accidents during their work (Bunn et al., 2005). Furthermore, professional truck drivers drive large vehicles, leading to relatively more severe consequences in case an accident occurs. In the United States alone, 333,000 large trucks (gross vehicle weight rating greater than 4.5 tons) were involved in traffic crashes during 2012. These crashes resulted in 3,921 fatalities and 104,000 people injuries

(NHTSA, 2012). In developing countries, where trucks commonly share the road with pedestrians and motorized two-wheeled vehicles, the situation is even more severe. For example, in India more than 231,000 people are killed in road traffic crashes annually (WHO, 2013). Approximately 35% of these fatal accidents involve heavy motor vehicles such as trucks (Kanchan et al., 2012). Besides the obvious direct consequences of these accidents such as lost lives, injuries, and liabilities, unsafe driving practices and accidents can also result in disrupted operations, reputation damage, driver absence due to injuries, increased vehicle maintenance and insurance costs, late customer deliveries, and overhead costs for incident investigation and follow-ups. Because of this, reducing the number of truck accidents through a focus on safe driving is of utmost importance.

Infrastructural improvements, technological advancements, and the alteration of traffic rules have contributed to a higher level of safety for truck drivers (Hauer, 1997), but at the same time it has become increasingly clear that preventive measures should also focus on the principal agent of long-haul transport: the driver (Dewar and Olson, 2007; Shinar, 2007). Nowadays, truck drivers should not only have driving skills but also have to be able to carry out other tasks during their trips. They have to address technical problems, take care of administration, route and delivery planning, communicating with the transport company and the customers, searching for pick-up cargo, and all of this while meeting client expectations in terms of timely delivery (European Agency for Safety and Health at Work, 2011). Operations practices such as just-in-time delivery can result in additional work pressure on drivers. Simultaneous management of all driving demands requires truck drivers to multitask, but the ability to successfully do this differs substantially between individuals (Watson and Strayer, 2010). Some people might be particularly able to combine conflicting demands, whereas others thrive better when confronted with more straightforward objectives. This suggests that taking driver-specific factors into account can help in explaining and improving safety and productivity in professional driving.

Estimates on the proportion of traffic accidents caused by human factors are consistently high, ranging from 90% (Lewin, 1982) to as high as 95% (Sabey and Taylor, 1980). It is therefore not surprising that several studies investigate the role of individual characteristics, such as the Big Five personality traits (Digman, 1990) and safety consciousness, in predicting dangerous driving behavior and accidents. For example, Oltedal and Rundmo (2006) demonstrated using surveys that personality traits and gender accounted for approximately 37% of the variance in risky driving behavior, Chen (2009) showed that drivers' attitude towards traffic safety directly related to risky driving behaviors, and according to Jones and Foreman (1985) unsafe bus drivers could be reliably distinguished from safe bus drivers based on their level of safety consciousness. As Elander et al. (1993) point out, these studies frequently employ methodologies such as driver self-reports of accidents or databases that do not offer detailed information. It is therefore essential to validate these findings using detailed and objective data sources.

Besides having to focus on driving safely, drivers are exposed to productivity targets that might conflict with safe driving behavior. Research on the link between driver characteristics and productivity is not abundant, but at the same time it is difficult to evaluate the safety performance of an individual or an organization without also taking productivity performance into account (Wolf, 2001). Several studies suggest that at least on the short term, trade-offs between productivity and safety exist (Brown et al., 2000; Cowing et al., 2004). At the same time, the relationship between safety and productivity on the longer term is unclear and the role of individual differences in this matter is largely unexplored.

This field study uses survey data measuring individual characteristics of 50 drivers combined with GPS data measuring highly detailed trip characteristics such as the duration, speed, and idle time of 403 trips on 78 distinct routes, with the objective to contribute to the literature on safety in operations management and transportation in three important ways. First, we explore the relationship between the personality and safety consciousness of truck drivers and their driving performance not only in terms of safety, but also in terms of productivity. Second, the unique combination of subjective survey measures and objective detailed GPS data addresses the common method bias that is often present in the research on this topic, leading to reliable conclusions based on rigorous testing. Third, the paper offers substantial practical value, as it assists operations managers to increase company performance by selecting drivers that are less likely to display unsafe or unproductive driving behavior. This should ultimately lead to safer and more productive operations.

6.2 Theory

Safety in professional driving

Worldwide, approximately 1.24 million people die in road traffic every year (WHO, 2013). This vast number, in addition to the numerous injuries resulting from road accidents, calls for research on the risk factors for road traffic injuries. Therefore, many different factors potentially related to road accidents (or road safety) have been studied. WHO (2004) has grouped these factors in four main categories: environmental factors influencing exposure to risk, personal risk factors influencing crash involvement, risk factors influencing crash severity, and risk factors influencing severity of post-crash injuries.

An example of a factor in the first category is demographics. Older drivers generally respond slower to potential hazards than younger drivers (Quimby and Watts, 1981), and more experienced drivers see themselves as more skilled in handling the car but less capable of driving safely (Lajunen and Summala, 1995). Also, differences between different groups of road users (such as cultural differences) have been linked to a higher accident risk (Elvik et al., 2009). The category of personal risk factors includes many potential predictors, such as personality of the driver (Lajunen and Summala, 1995), alcohol and/or drug use (Moskowitz and Robinson, 1988; Walsh et al., 2004), and fatigue (Akerstedt, 2000). The third category is, among other things, influenced by the crash protection measures used in the vehicle such as safety belts (Evans, 1996), and the speed of the vehicle at the time of the accident (Joksch, 1993). The severity of post-crash injuries, the fourth category, depends to a large extent on the medical infrastructure at the location of the crash

(Khorasani-Zavareh et al., 2009). In a professional setting, the safety culture, leadership, wage, turnover, and incentive system employed by the company may also influence accident risk in addition to the four aforementioned categories (Cantor et al., 2010; De Koster et al., 2011; De Vries et al., 2015; Rodriguez et al., 2006, 2003). All these factors can be grouped in three main groups: driver characteristics, vehicle characteristics, and environmental (including company) characteristics. In this paper we are particularly interested in identifying the relationship between driver characteristics such as driver personality and safety in professional driving.

Productivity in professional driving

Even though driving safely is a very important objective in professional driving, drivers always have to combine this objective with reaching their productivity targets. The productivity of professional delivery or truck drivers can be measured by the number of successfully delivered packages/loads per time unit. The determinants of productivity and efficiency of professional driving have been scarcely researched. However, we categorize the factors determining productivity professional driving also as driver characteristics, vehicle characteristics, and environmental characteristics. For example, productivity in professional driving is also influenced by vehicle characteristics like the presence of satellite communication systems (Belman and Monaco, 2001), environmental/company characteristics such as goal-setting and incentive systems (LaMere et al., 1996), and turnover (Keller, 2002). We expect that driver characteristics such as the personality of individual drivers relate to productivity in professional driving as well.

Driver characteristics: the relationship between personality traits and driving performance

Different drivers have a different personality, and these differences in personality are likely to explain part of the variance in performance between drivers. The five-factor model, which describes the personality of individuals in terms of ‘extraversion’, ‘conscientiousness’, ‘agreeableness’, ‘openness’, and ‘neuroticism’, can be considered as the most important model describing personality (Digman, 1990). Barrick and Mount (1991) provide examples of traits commonly linked to each of the five factors. *Extravert* people are mostly viewed as assertive, talkative, and active. Highly *conscientious* people are generally viewed as responsible, persevering, thorough, and organized. Highly a*greeable* people are commonly seen as flexible, tolerant, cooperative, and trusting. Highly *open* people are often regarded as being curious, broad-minded, original, and imaginative. Highly *neurotic* people are usually seen as depressed, insecure, emotional, and worried. A considerable number of studies has investigated the relationship between personality traits and general job performance.

Productivity: Based on a quantitative summary of 15 meta-analyses investigating the relationship between the five-factor model and job performance Barrick et al. (2001) concluded that conscientiousness (positively) and neuroticism (negatively) are consistently predicting overall work performance across all studied occupations. The measure of overall work performance is based on supervisory performance ratings and objective productivity data. Agreeableness, openness, and extraversion have only been linked to performance in specific occupational environments. Even though these studies did not focus on the context of professional driving specifically, this finding leads us to expect that conscientiousness and neuroticism have a similar relationship with performance in the context of our study. This is stated in hypothesis 1 and 2:

H1: *Professional drivers scoring higher on conscientiousness are more productive.*

H2: *Professional drivers scoring higher on neuroticism are less productive.*

Safety: The relationship between the big-five personality traits and driving safety has been investigated more extensively, but results have been inconclusive. Clarke and Robertson (2005) and Sümer et al. (2005) suggested that neuroticism was associated with a higher accident risk because of its relation with stress. Pestonjee and Singh (1980) performed an empirical examination of the correlation between personality traits (neuroticism and extraversion) and road accidents and found that more extravert drivers were involved in significantly more accidents. Elander et al. (1993) found that while training and experience can improve the skills of a driver the personality and antisocial motivation also affects the driving style, but Lester (1991) concluded based on a synthesis of nine studies that neither of the five factors significantly relates to involvement in accidents. Arthur and Graziano (1996) found that more conscientious drivers reported to have been involved in fewer driving accidents than less conscientious drivers, whereas Cellar et al. (2000) identified agreeableness to be negatively correlated to the number of driving accidents and speeding tickets. The large majority of these studies rely on self-reports of accidents or risky driving behavior, which are relatively easy to obtain and might include relatively detailed information, but also suffer from several methodological biases (Elander et al., 1993). For example, drivers might not accurately remember events that have taken place in the further past, and certain people might be more willing to report negative events like accidents than other people. On the other hand, official databases containing objective accident numbers do usually not include information on minor accidents, whereas more severe accidents are relatively rare. This makes it more difficult to establish statistical relationships. Furthermore, data from official databases can usually not be linked to individuals, making it impossible to find out more about the potential relationship between accidents and specific individual characteristics of the driver. We believe that these measurement issues could be responsible for at least part of the inconclusive results regarding the role of personality traits in predicting accidents and risky driving behavior identified in earlier studies. Therefore, we aim to explore the relationship between individual driver characteristics and driving safety using a method less susceptible to bias. Şimşek et al. (2013) demonstrated the potential value of Global Positioning Systems (GPS) in measuring the performance of professional drivers, but did not take the individual characteristics of the drivers into consideration. Zhao et al. (2014) used GPS surveillance to show that individual characteristics of taxi drivers significantly correlate with accident numbers and the maximum vehicle speed, but did not make use of survey measures to include behavioral constructs such as personality characteristics in their study. In the present study, we explore the relationship between the well-established five-factor model of personality and objective measures of driving productivity and driving safety. Because of the inconclusive findings in earlier studies we do not have hypotheses about the relationship between specific personality traits and driving safety, but we will still explore this relationship in the current study.

Driver characteristics: safety consciousness

Even though it is difficult to hypothesize a specific relationship between any of the personality traits and driving safety, other individual characteristics exist that have been established as predictors of safety. Especially the safety consciousness of individuals has been related to fewer injuries or accidents across work and non-work domains (Das et al., 2008; Kelloway et al., 2006; Westaby and Lee, 2003; Zhao et al., 2014). Safety consciousness can be defined as the awareness of individuals about safety issues (Barling et al., 2002). An important difference between the safety consciousness of individuals and their personality traits is that personality traits are relatively stable, whereas safety consciousness can be more easily influenced by workplace factors such as leadership (Barling et al., 2002). This is an important difference, because it implies that companies do not only have the opportunity to select new personnel that is more likely to display safe working behavior, but that companies can also increase this likelihood through training and management of their existing personnel. Therefore, we investigate the relationship between the safety consciousness of long-haul truck drivers and their driving safety as well. In doing so, we expect to identify a positive relationship between these two constructs:

H3: *Professional drivers scoring higher on safety consciousness drive more safely.*

The full conceptual model, which includes the expected relations between conscientiousness and driving productivity, neuroticism and driving productivity, and safety consciousness and driving safety, is displayed in Figure 9.

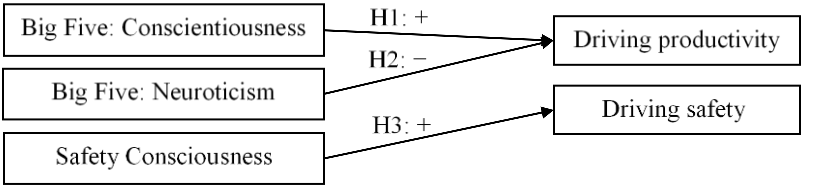

Figure 9: Conceptual model

6.3 Methodology

Data collection

To investigate the relationship between driver characteristics and objective performance outcomes, we collected data at a major transport company in India. In India approximately 65% of all freight transport is carried by roads (National Highways Authority of India, 2015), and these roads suffer from serious congestion problems. Even on highways trucks are only able to drive an average of approximately 35 km/h (Gupta et al., 2010; Sen et al., 2013). This makes combining productive driving with safe driving especially challenging, and offers a suitable research context for the current study. The company operates on more than 500 routes on a daily basis with more than 520 owned trucks. The vehicles include trailer-trucks, dry container trucks, and refrigerated vehicles. They handle the transport of FMCG, Food and Beverages, Automobiles, white goods and Electronic products. All vehicles used for data collection in this study are 32 ft. multi-axle rigid trucks (such as the truck displayed in Figure 10) manufactured in 2009 or later, transporting non-hazardous goods. All vehicles were equipped with similar systems (i.e. they did not differ in terms of on-board technology) and had a gross weight of 25 tons. Restricting the study to drivers within one specific company and a single truck type enables us to limit the variation in other factors than the driver (e.g. company culture, infrastructure, type and maintenance state of trucks) that may influence productivity and safety to a minimum.

Figure 10: Example of 32 ft. multi-axle rigid vehicle

Two sources of data are used: the transport company's ERP database and the GPS database. Note that we consider one-way freight trips, and a driver may travel via multiple routes between the origin and destination point. A substantial amount of time is spent by the driver at the loading and unloading point corresponding to the customer goods pick-up and destination location. Since the time spent at the loading and unloading point is beyond the driver's control, we do not include the loading and unloading times in the trip data. This means the measurement of the trip begins immediately after the truck is loaded with goods and the trip ends immediately after the truck reaches the customer's destination location. For each trip, the approximate time of truck departure from the loading point to the truck arrival and the destination unloading point were gathered from the ERP system. Using these time estimates, precise dispatch and arrival times were gathered by analyzing the GPS data of the corresponding trip from the GPS database. The GPS database delivered detailed trip information, with data recorded every 4 km. Subsequently, the trip details such as speed at every point of measurement, stoppage details, and the distance details were then obtained from the GPS database. Further trip details such as client, route details, and the master data about the vehicle and route were appended from the company's ERP system. In total, data were collected for 403 trips across 78 different routes. The frequency distribution of trips per route shows that no single route accounts for more than 19 trips (see Figure 11). All trips originated from one of the branch offices (indicated by black dots in Figure 12). The average distance driven on these trips was 1,474 km (sd = 785 km), the average driving time was 2,419 minutes (sd = 1,250 minutes), and the average total time taken was 5,816 minutes (sd = 3,449 minutes). Given the resolution of one measurement per 4 km, approximately 370 measurements were performed on the average trip. Figure 13 displays an overview of the different sources of data.

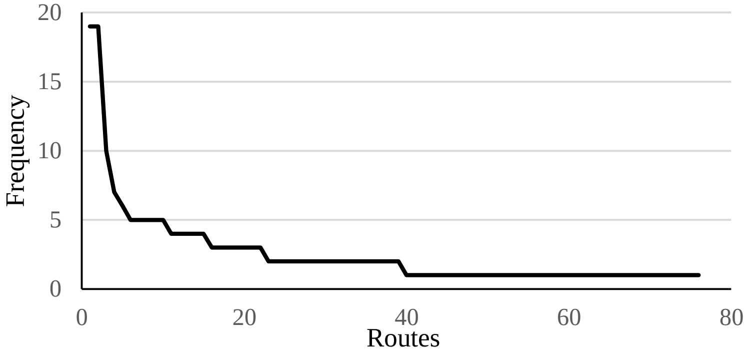

Figure 11: Frequency distribution of trips per route

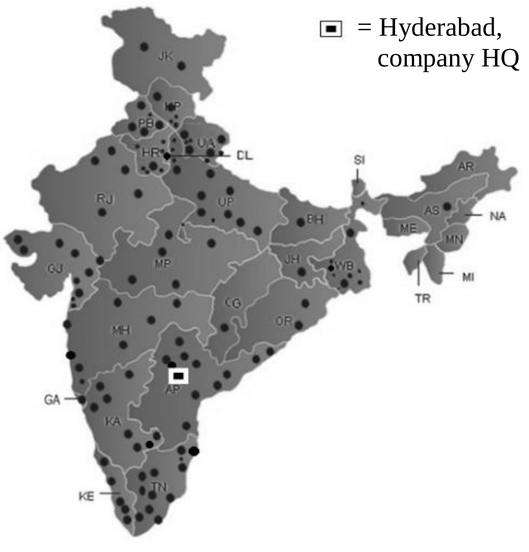

Figure 12: Overview company branch offices and headquarters

Participants

The drivers were randomly recruited by a neutral employee (not a manager of the drivers) working for the company. Only drivers who visited the main headquarters in Hyderabad (as origin or destination of their trip, or in a subsequent trip) could be recruited, because the driver characteristics measures were obtained there. Additionally, only drivers with at least one month of working experience in the company were included in the pool of participants to have sufficient data about the trips completed during the month before. Approximately 20% of all 500 drivers in the company work from the Hyderabad headquarters. Fifty drivers participated in the study. For three drivers, data of only one trip were collected. For the rest of the drivers, data of multiple trips were available (maximum 10 trips, 7 on average). 51% of the drivers were between 22 and 35 years old, and only 10.2% were older than 50. 87.8% of the drivers worked as a driver for at least 5 years, and 51% of the drivers for more than 10 years.

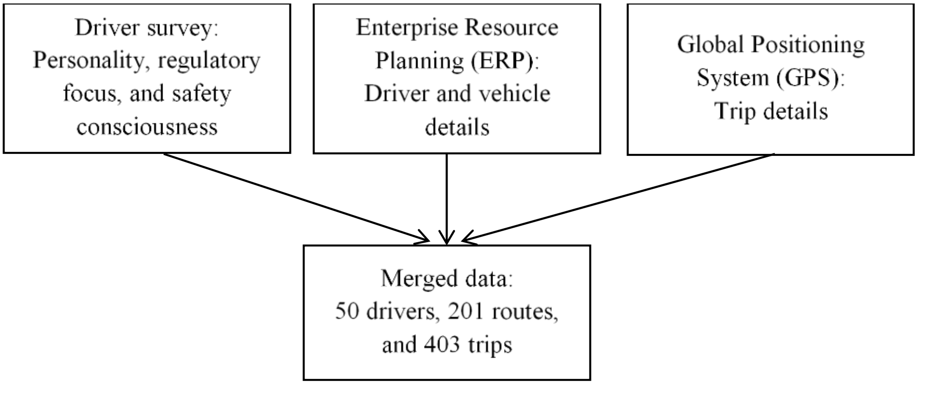

Figure 13: Data sources and processing

Operationalizations outcome variables

In this study we operationalize driving safety by the *number of times a driver drove faster than 70 km/h per kilometer driven*. Driving faster than 70 km/h is a definite speed violation in India since the maximum speed for heavy goods vehicles is limited to 65 km/h, even on four-lane roads and national highways (Express News Service, 2014). In addition, national highways only account for approximately 1.7% of the complete road network in India (National Highways Authority of India, 2015). Measuring the number of violations was preferred over the percentage of time a driver drove faster than 70 km/h since speed volatility better reflects risky driving behavior (Deffenbacher et al., 2003). Also the number of times drivers exceeded 50 km/h and 60 km/h were examined, to verify that this delivers similar results. The choice to operationalize driving safety in terms of speed violations instead of accidents offers several advantages. First of all, as is explained in the literature review, accidents can be the result of driver-specific characteristics, vehicle characteristics, environmental characteristics, or a combination of these factors. Thus, a considerable share of accidents is caused by factors completely beyond the influence of the driver, and should be prevented by focusing on other aspects. However, these accidents create a noise in the data that makes it more difficult to discover relations between individual driver characteristics and accidents that are caused by the driver. Secondly, the relatively rare occurrence of accidents makes it nearly impossible to select a sufficient number of cases in which the factors that are not related to the individual driver (e.g. vehicle type, culture, infrastructure) are constant. The current operationalization overcomes these problems because committing a speed violation is virtually always caused by the behavior of the driver, it occurs relatively frequently, and is a closer proxy of unsafe driving behavior than accidents.

Productivity in transportation is generally operationalized as the number of deliveries per time unit, or conversely, as the time taken per delivery. In this study, the *inverse of the driving time relative to the Google Maps time estimate* for a specific route served as a measure for driving productivity. To arrive at this measure, the Google Maps time estimate (without traffic) was subtracted from the driving time, and the resulting number was divided by the Google Maps estimate. This measure uses net driving time, as stoppages are not included in this measure. It should be noted that the 403 trips have taken place on 78 different routes and at different moments. Google Maps accounts for differences in road conditions, but factors such as rush hours and a higher traffic density around cities could potentially confound the results. However, we expect that the fact that all trips are multi-day trips levels out these rush-hour effects, because every driver will be driving during both non-rush and rush hours. Furthermore, all trips start and end at locations outside of city centers, and we control for the percentage in distance of the trip covered during night time (see ‘control variables’).

Operationalizing independent variables

We used a survey to measure safety consciousness and personality. Because of illiteracy in Hindi among the truck drivers, a neutral person within the company (not a manager or direct colleague of the drivers) administered the survey. Before use in data collection, the scales were translated to Hindi and back-translated to English to establish that the translation was accurate. The scales used to measure safety consciousness and personality are provided in the following sections.

Safety consciousness

Barling et al.’s (2002) safety consciousness scale was used to measure safety consciousness. Each of the seven items was rated using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The items have been adapted to be more accurately applicable to the transport situation. The complete scale is displayed in Table 29. Most likely because of translation issues, item 3 suppressed the scale’s reliability and was therefore removed from the measure in this study. Consequently, safety consciousness was measured by the average of the remaining items ($\alpha = .70$).

Table 29: Barling et al.’s safety consciousness scale

1.	I always wear the protective equipment or clothing required by my job (e.g. Safety belt, safety shoes, gloves etc.)
2.	I am well aware of the safety risks involved in my job

3,	I know where the safety equipment are located in my truck (such as fire extinguishers, first aid kits, safety triangles, safety cones, safety vests)
4.	I do not use equipment at work that I feel is unsafe
5.	I inform management of any potential hazards I notice on the job
6.	I know what procedures to follow if injured on my trip
7.	I would know what to do if an emergency occurred on my trips (e.g., fire or accident)

Personality

The Big Five Inventory (BFI) (Benet-Martinez and John, 1998; John et al., 1991, Table 17) was used to measure the personality traits of the truck drivers. According to Schmitt et al. (2007), the BFI structure is highly replicable across all major cultural regions. Participants had to rate each of the items using a five-point Likert scale. To arrive at acceptable reliability levels of the personality subscales, several items had to be deleted. The resulting reliability of the subscales measuring conscientiousness (items 18 and 43 deleted, $\alpha = .77$), openness (items 35 and 41 deleted, $\alpha = .79$), agreeableness (items 2 and 27 deleted, $\alpha = .69$), and extraversion (items 1 and 6 deleted, $\alpha = .61$) was acceptable for use in exploratory research (Nunnally et al., 1967). The neuroticism subscale was not suitable to be used in subsequent analyses due to low reliability ($\alpha = .550$), which could not be improved by deleting items from the scale.

Control variables

Several control variables were employed to account for the differences between drivers and trips that could influence the outcome variables:

<u>Driver level:</u> The number of years a driver had been working as a driver was employed to control for the experience of the drivers.

<u>Trip level:</u> Two variables were used to account for the differences between the routes: the percentage of distance of the trip that was covered during night time, and the average speed estimated by Google Maps along the entire route. These two variables should account for the largest part of the structural variance between trips. Google maps accounts for the

differences in road types encountered during the trip, and the percentage of the trip covered during night time accounts for the lack of traffic during the night.

6.4 Results

Descriptives

First, the descriptive statistics of all variables and the correlations between them were computed. on driver level (Table 30) and on trip level (Table 31).

Table 30: Descriptive statistics and correlations of drivers

	Variable	Mean	Standard deviation	1	2	3	4	5	6	7
1	Work experience as driver	12.16	7.91	-						
2	Safety consciousness	4.04	.38	.20	*.70*					
3	BFI: Extraversion	3.79	.36	.08	.33*	*.61*				
4	BFI: Agreeableness	4.17	.24	.17	.15	.24	*.70*			
5	BFI: Neuroticism	1.83	.30	-.31*	-.41**	-.25	.05	*.55*		
6	BFI: Openness	2.75	.42	.03	.39**	.367**	.05	-.39**	.79	
7	BFI: Conscientiousness	4.30	.27	.09	.25	.05	.28*	-.30*	.38**	*.77*

N = 50. *p < .05, **p < .01. Cronbach's α is displayed in italics on the diagonal of the relevant variables.

On driver level, this reveals significant correlations between some of the BFI personality traits. On trip level, the correlations demonstrate the importance of employing the percentage of distance of the trip covered during night time and the expected average speed on Google Maps as control variables in the subsequent analyses. These variables correlate highly with most dependent variables, and controlling for them could facilitate the identification of predictors of productivity and safety that are relevant to the current study. Linear mixed effects models were used to analyze the data in SPSS 22 (IBM Corp., 2012) to account for the multiple observations per driver and hierarchical characteristics of the dataset (Hardgrave et al., 2013). To assess the influence of the non-independence among the multiple observations per driver, models with random (driver) intercepts were compared with the models without this intercept using likelihood-ratio tests based on Restricted Maximum Likelihood (REML) estimation (West et al., 2014). This test (Table 32) confirmed that a random intercept accounting for driver-specific effects explains a significant part of the variance in the dependent variable, and is therefore included in all subsequent analyses.

Table 31: Descriptive statistics and correlations of trips

	Variable	Mean	Standard deviation	1	2	3	4	5
1	Number of speed violations (>70 km/h) per km	0.01	0.02					
2	Average driving speed (km/h)	36.46	4.02	.46**				
3	Drive time minus Google Maps time per Google Maps time	0.85	0.261	-.18**	-.65**			
4	% distance of trip covered during night time	24.32	12.5	.17**	.31**	-.22**		
5	Expected average speed Google Maps (km/min)	1.09	0.08	.14**	.10*	.46**	-0.01	
6	Square root of trip time	72.89	22.45	.15**	-0.02	.30**	0.02	.37**

N = 403. $^*p < .05$, $^{**}p < .01$

Table 32: Likelihood ratio test, comparison between models with and without random intercept

	-2 log likelihood with random intercept	-2 log likelihood without random intercept	Δ -2 log likelihood	p-value likelihood ratio test
Inverse of drive time minus Google Maps time per Google Maps time	810.16	930.27	120.11	>.01
Number of speed violations (>70 km/h) per km	950.52	1045.95	95.43	>.01

$^{**}p < .01$

Productivity

In predicting the inverse of the drive time relative to the Google Maps time (Table 33), we controlled for the “work experience as driver” and “percentage of the trip distance covered during night time”.

Table 33: Linear mixed effects models predicting driving productivity

	Reverse of drive time (relative to Google Maps estimate)		
Parameter	Standardized estimate	*df*	*T*
Intercept	0.01	38.87	0.06
Work experience as driver	-0.14	39.93	-1.28
% distance of trip covered during nighttime	0.09	363.01	**1.69†**
Safety consciousness	0.29	41.74	**2.37***
BFI: Conscientiousness	-0.02	38.92	-0.19
BFI: Extraversion	-0.28	40.51	**-2.43***
BFI: Agreeableness	-0.06	38.52	-0.59
BFI: Neuroticism	0.07	42.24	0.53
BFI: Openness	0.14	39.23	1.2
Conditional R-squared	0.63		
Marginal R-squared	0.31		

** $p < .01$, * $p < .05$, † $p < .10$

In the resulting model, Safety Consciousness and Extraversion emerged as significant predictors. More safety conscious drivers tend to take shorter time (relative to the Google Maps estimate) than less safety conscious drivers. More extravert drivers, on the other hand, tend to take relatively more time. The marginal and conditional R^2 as described by Nakagawa and Schielzeth (2013) were calculated using the MuMIn (Barton, 2015) package in R 3.0.1 (R Core Team, 2013) to estimate model fit. In this model the fixed factors (allowed to vary per trip) explain 31% of the variance in drive time relative to Google Maps time (marginal R^2), and the entire model (fixed effects + random intercept accounting for the individual drivers) explains 63% of the variance (conditional R^2). The results are not in line with hypotheses 1 and 2, since we did not find the hypothesized positive relationship between conscientiousness and driving productivity or hypothesized negative relationship between neuroticism and driving productivity.

To investigate the impact of safety consciousness on productivity more thoroughly, we compared the driving speed of the 15 drivers scoring the highest on safety consciousness with the 15 drivers scoring the lowest on safety consciousness using a linear mixed-effects model. In measuring the average driving speed, stoppages were not included. A dummy variable was used to indicate whether drivers belonged to the groups scoring high or low (or neither) on safety consciousness. Working experience as a driver and the percentage of trip distance covered during night time were again employed as control variables. The results (Table 34) show that the drivers with a relatively high score on safety consciousness drive on average 2.64 km/h (or 7.5%) faster during all their trips than drivers with a relatively low score on safety consciousness. Since the average driving time in our sample is 2419 minutes, this translates to average time savings of 181 minutes.

Table 34: Average driving speed of the top 15 versus bottom 15 safety conscious drivers

	Top 15 safety conscious drivers		Bottom 15 safety conscious drivers		Pairwise comparison	
	Mean	*SD*	*Mean*	*SD*	*F*	*p*
Safety consciousness	4.45	0.05	3.62	0.05	169	<.01
Average driving speed	37.84	0.72	35.2	0.82	5.94	0.02

Comparing top 15 with bottom 15 while controlling for working experience as a driver and percentage of trip distance covered during night time.

Safety

In predicting the number of speed violations per km (Table 35) “work experience as driver” is the only control variable that displays a marginally significant trend, with more experienced drivers violating the speed limit less frequently than less experienced drivers. After controlling for this, more conscientious drivers make significantly more speed violations per km than less conscientious drivers. In this model, the fixed factors explain 8% of the variance in the number of speed violations per km, whereas the entire model explains 42% of the variance. The finding that more conscientious drivers make more speed violations is noteworthy, given that conscientiousness is consistently linked to positive outcomes in work-related contexts (Dudley et al., 2006). The results do not support the expectations stated in hypothesis 3, since we did not identify a relationship between safety consciousness and safe driving behavior.

Table 35: Linear mixed effects models predicting driving safety

Parameter	Number of speed violations (>70 km/h) per km: Standardized estimate	*df*	*F*
Intercept	-0.04	42.55	-0.44
Square root of total trip time	-	-	-
Work experience as driver	-0.18	44.12	**-1.73†**
% distance of trip covered during nighttime	0.03	363	0.59
Expected average speed Google Maps (km/min)	-0.05	352.25	-1.13
Safety consciousness	0.09	45.99	0.76
BFI: Conscientiousness	0.21	42.86	**2.13***
BFI: Extraversion	-0.02	44.72	-0.22
BFI: Agreeableness	-0.01	42.22	-0.13
BFI: Neuroticism	0	46.44	-0.01
BFI: Openness	0.03	43.05	0.27
Conditional R-Squared		0.42	
Marginal R-Squared		0.08	

** $p < .01$, * $p < .05$, † $p < .10$

Similar to the procedure followed for driving productivity, we investigated the impact of conscientiousness on dangerous driving behavior more closely by comparing the 15 drivers scoring the highest on conscientiousness with the 15 drivers scoring the lowest on conscientiousness using a linear mixed-effects model (Table 36).

Table 36: Average number of speed violations per 100 km driven of the top 15 versus bottom 15 conscientious drivers

	Top 15 conscientious drivers		Bottom 15 conscientious drivers		Pairwise comparison	
	Mean	*SD*	*Mean*	*SD*	F	*p*
Conscientiousness	4.05	0.1	4.63	0.08	15.76	<.01
Speed violations per 100 km driven	1.61	0.23	0.47	0.23	11.26	<.01

Comparing top 15 with bottom 15 while controlling for working experience as a driver and percentage of trip distance covered during night time.

Again, we controlled for working experience as a driver and the percentage of trip distance covered during night time. The results (Table 36) show that the drivers with a relatively low score on conscientiousness make on average 0.47 speed violations per 100 km driven. The drivers scoring relatively high on conscientiousness make on average 1.61 violations during the same distance, more than three times as many.

As additional analyses, we also investigated whether some predictors relate to productivity and safety simultaneously. To do this, the product of "the inverse of the drive time minus Google Maps time per Google Maps time" and the "Number of speed violations (>70 km/h) per km" was employed as dependent variable. None of the predictors accounted for a significant proportion of the variance in this dependent variable. Furthermore, we tested whether adding safety as to the model predicting productivity influenced the other predictors, but this did not yield any additional insights.

Necessary Condition Analysis

Our finding that more safety conscious drivers appear to drive more productively without making more speed violations or taking fewer stops is a surprising outcome that deserves to be investigated more closely. Inspection of a scatterplot (Figure 14) with the aggregated productivity per driver in terms of the drive time relative to the Google Maps estimate (controlled for the percentage of the trip distance covered during night time and work experience as driver using the estimated marginal means) on the y-axis and safety consciousness on the x-axis reveals a relatively large empty top-left corner. This suggests that, at least in the current dataset, drivers could not achieve high levels of productivity with low levels of safety consciousness. An assumption of the mixed-effects models employed to analyze the data is that all independent variables can contribute to the outcome and can possibly contribute to each other, without a single predictor being a bottleneck blocking an increase in the outcome variable (Dul, 2015). However, this assumption is not always accurate.

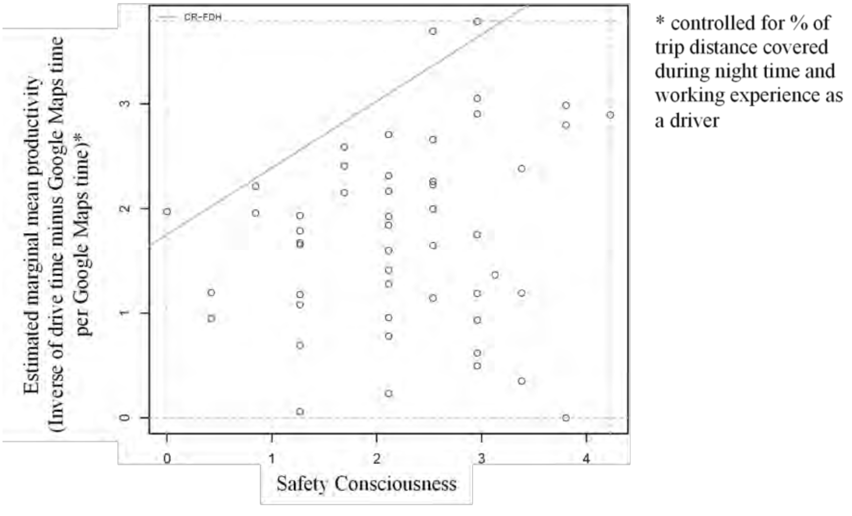

Figure 14: Scatterplot Necessary Condition Analysis (NCA)

Theoretically it is also strange in our case to assume that a higher level of safety consciousness continuously relates to a higher level of productivity, especially when considering that a strong emphasis on safety of an individual could divert his or her attention away from driving productively. However, a certain degree of safety consciousness might be required to handle risky and dangerous situations on the road more effectively and therefore quicker. On long-haul trips in India such risky and dangerous events do unavoidably occur, and drivers need to be prepared to handle them well. We therefore expect that a certain minimum level of safety consciousness is necessary for truck drivers to be well-prepared to handle perilous situations they might encounter more effectively. To test this we complement our mixed-effects model with a Necessary Condition Analysis (NCA), a technique to identify if necessary conditions exist in datasets (Dul, 2015).

Following the stepwise approach described by Dul (2015), we executed an NCA to find out if a certain level of safety consciousness is required to achieve high productivity in our dataset. As a first step, we added a ceiling regression line to the scatter plot using the Ceiling Regression-FDH method (going through the upper-left edges of a Free Disposal Hull envelopment line), because a straight line fits the data points around the ceiling relatively well. To quantify the effect size of the necessary condition, we first calculate the size of the empty space above the ceiling line in the scatterplot and divide it by the scope, the total surface of the plot between the maximum and minimum observed values. This results (Table 37) in an effect size of .20, which can be considered as a medium effect according to the criteria proposed by Dul (2015).

Table 37: Results Necessary Condition Analysis (NCA)

Ceiling zone	3.262
Scope	16.02
Ceiling line	Yc = .6369 Xc + 1.752
Accuracy	94%
Effect size	.20*
Condition inefficiency	24%
Outcome inefficiency	46%

*N = 50, * d ≥ .1*

The outcome inefficiency of 46% indicates that for a productivity score at 46% of the maximum observed productivity, any value of safety consciousness allows for a higher value of productivity (represented by the intercept of the y-axis in the plot). The results of the NCA suggest that in these data a certain minimum level of safety consciousness is necessary for truck drivers to achieve top productivity results. If this minimum level is not achieved, the relatively low level of safety consciousness might prevent an increase of productivity following from other predictors.

6.5 Conclusion and discussion

The vast number of traffic accidents involving trucks and the often severe consequences of such accidents emphasize the relevance of research focusing on safe driving behavior of truck drivers. This study complements the existing literature on the relationship between individual driver characteristics and driving safety in several ways.

First, this study makes use of objective data instead of subjective self-reports to operationalize the outcome variables. The high level of detail of these objective measurements allow us to draw more reliable and robust conclusions, not subject to common-method bias.

Second, because drivers are not only facing the requirement to drive safely but also productively, we have examined the relationship between individual driver characteristics and productivity as well. Third, we have provided clear illustrations of the practical impact of safety consciousness and conscientiousness on safe driving behavior and productivity. These insights can be employed by (transport) operations managers in the selection and training of employees.

Implications for researchers. In this study we did not find support for the expected positive relation between conscientiousness and productivity (H1), the expected negative relation between neuroticism and productivity (H2), and the expected positive relation between consciousness and safety behavior (H3). However, we believe that the identified absence of these relationships offers important insights as well. For example, the absence of a relationship between safety consciousness and safety behavior is a vital finding that could put the existing research on safety consciousness in a different perspective. Most examples of studies that report a positive relation between safety consciousness and safety make use of self-reported safety-outcomes (Barling et al., 2002; Kelloway et al., 2006; Westaby and Lee, 2003), whereas the absence of this relation that we identified in the current study aligns with the finding of (De Koster et al., 2011), who also made use of objective measures of safety outcomes. This highlights that it is important to revisit the relationship between safety consciousness and safety outcomes through additional research that makes use of objective safety outcomes.

At the same time, we have identified that a higher level of safety consciousness of long-haul truck drivers relates to a higher level of productivity. This finding is surprising, as the link between safety consciousness and productivity is not immediately evident. We believe that during long trips on Indian roads it is inevitable that drivers encounter hazardous situations. Knowing how to respond appropriately to these situations does not only potentially prevent accidents, but can also result in valuable time-savings. Another potential explanation could be that more safety conscious drivers are better in planning their route to avoid major traffic jams, leading to a shorter trip time. Furthermore, even though we did not identify the hypothesized expected positive relationship between safety consciousness and driving safety (H3), a negative tradeoff between safety behaviors and productivity was also not identified. Based on these results we therefore still believe that this finding is in line with Pagell et al.'s (2014, 2015) conclusion that it is possible to combine safe operations with productive operations.

Furthermore, we did not find the hypothesized positive relationship between conscientiousness and productivity (H1). Even though conscientiousness is commonly linked to higher productivity (Barrick et al., 2001), more conscientious drivers do somehow not manage to finish their trips faster. Instead, we found that more conscientious drivers display more dangerous driving behavior. This could be caused by a high perceived time-pressure to meet their productivity targets, which results in compromising on safety on certain occasions without the desired productivity gains. The realization that conscientiousness could also relate to unwanted aspects of job performance is a worthwhile contribution as well.

Implications for operations management practice. This study offers a new avenue to improve driving productivity by identifying the right kind of drivers for long-haul trips. Companies can employ personality tests to assess the level of a driver’s safety consciousness in the hiring process, or offer suitable training to drivers to improve their level of safety consciousness. Furthermore, operations managers can select specific drivers to meet the targets of a specific trip. For example, for trips with more time sensitive delivery demands it could be suitable to select more safety conscious drivers. By managing operational risks more effectively, safety conscious drivers can identify the threats and vulnerabilities and reduce unproductive time in the long run. A reduced-risk environment is also a productive environment. Therefore, considering safety consciousness in personnel selection and training should result in a workforce of drivers who are more capable of managing operational risks without simultaneously committing a higher number of speeding violations, thus being able to combine driving productively with driving safely.

Additionally, the study shows that drivers scoring higher on conscientiousness display more risky driving behavior. This is likely caused by a strong (but unsuccessful) focus of these drivers on reaching their productivity goals. Using a personality test this can be identified during the recruitment stage as well, enabling operations managers to pay extra attention to the way in which the productivity goals are presented and emphasized to these drivers. Furthermore, operations managers can use this information to avoid that highly conscientious drivers are assigned to trips on routes that are known to be relatively dangerous.

Strengths and limitations

We can identify several strengths and limitations in this study. First of all, the sample size of 50 drivers is relatively small. However, this is largely compensated by the fact that for most drivers measurements were obtained for multiple trips.

Second, regarding the safety operationalization, we did not directly relate the individual characteristics of the drivers to accidents. Instead, we employed measures of risky driving behaviors such as committing fewer speed violations and taking less rest as proxies for driving safety. The disadvantage is that, even though the relationship between risky driving behavior and accidents has been established in previous studies (e.g. Fergusson et al., 2003; Oltedal and Rundmo, 2006), we have to assume that these behaviors indeed result in more accidents. The advantage of our approach is that accidents occur much less frequently than unsafe driving behaviors, and it is to a large degree unpredictable when unsafe driving behavior results in an accident. Therefore, measuring risky driving behavior offers a measure of driving safety that is more directly related to the driver and less susceptible to external factors.

Third, the setting of long-haul driving in India is unique in terms of the traffic density and high accident risk. We believe that even though the results best represent the Indian context, the identified relationships should also hold in other environments that can be characterized by a high traffic density and accident risk, long distances, relatively undeveloped infrastructure, and many different types of road users. However, it remains not entirely clear to what extent the results of this study can be generalized to traffic settings in more developed countries.

Concluding, this exploration of the relationship between individual driver characteristics and productivity and safety outcomes contributes to the rich literature on (occupational) road safety and accident prevention. By making use of objective outcome measures which include data collected through the ERP-system, the GPS-module, and driver surveys, we have been able to obtain practically relevant results that are based on a methodologically rigorous approach.

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Chapter 7

Summary and Conclusions

This dissertation studies the influence of behavioral factors on processes within logistics and intra-logistics, it provides an illustration of the potential impact of these behavioral factors on essential operational outcomes such as safety, productivity, and quality. Through a combination of realistic, yet rigorous, behavioral experiments and survey research, we provide evidence that behavioral aspects and differences between individuals account for a significant part of the variance in performance of logistical processes. Existing models that are intended to improve or optimize logistical processes usually do not take these behavioral aspects into account. For these models, a relaxation of the assumption that all individuals working in an operational context are hyper-rational would offer a more accurate reflection of reality, potentially leading to more accurate and generalizable predictions.

In the following sections we discuss the main findings and contribution of each individual chapter. Then, we discuss the scientific and managerial relevance of the dissertations as a whole and provide some potential avenues for future research.

7.1 Summary of main findings and contributions

Chapter 2. Aligning Order Picking Methods, Incentive Systems, and Regulatory Focus to Increase Performance

This chapter focused on order picking to demonstrate that the performance of operational processes frequently depends not only on efficient layouts and methods, but also on effectively combining these design aspects with motivational aspects such as incentive systems and individual characteristics of employees such as regulatory focus. This was achieved in a behavioral experiment in a realistic field setting, which, as pointed out by Bendoly et al. (2006), offers the opportunity to observe natural behavior under different conditions without compromising on generalizability. We found that, by aligning order picking methods, incentive systems and regulatory focus, warehouses can substantially improve productivity. More specifically, the results show that in parallel picking, competition-based incentives deliver significantly higher productivity than cooperation-based incentives for promotion-focused individuals, but not for prevention-focused individuals. In contrast, in zone picking, cooperation-based incentives delivered higher productivity for prevention- and promotion-focused individuals. In dynamic zone picking, no differences between the two incentive systems were identified for participants with a prevention-focus as well as for participants with a promotion focus. This suggests that in terms of interdependence, dynamic zone picking can be placed on a scale somewhere between parallel and zone picking. No effects of the independent variables on picking quality were identified.

Chapter 3. Pick One for the Team: The Effect of Individual and Team Incentives on Parallel and Zone Order Picking Performance

In chapter 3 we extended the findings of chapter 2 in two ways. First, we investigated whether similar effects could be identified in a different environment and setup. Therefore this experiment was carried out in a more abstract laboratory setting, instead of the realistic warehouse setup. Second, instead of cooperative and competitive incentive systems, this study examined the effect of individual and team incentive systems. To a large extent, the results replicated the findings of chapter 2 with regards to the effects of cooperative and competitive incentives for zone picking. However, for parallel picking no differences in productivity between individual and team incentives were found. This demonstrates not only that an individual evaluation of performance is essential for an incentive system applied to an independent task, but that a competitive element can be important to motivate employees as well.

Chapter 4. Exploring the role of picker personality in predicting picking performance with pick by voice, pick to light, and RF-terminal picking.

Chapter 4 extended the previous two chapters by incorporating another important aspect of order picking: the order picking tool. In a similar setup as in chapter 2, we found that picking performance with different order picking tools is at least partly dependent on the personality and other individual characteristics of the individual pickers. Consistent with most literature on the relationship between the Big Five personality traits (Hurtz and Donovan, 2000), a higher level of conscientiousness related to higher productivity in voice picking, but not in RF-terminal picking and pick to light. Higher levels of neuroticism, extraversion, and a greater age related to a higher error percentage. Furthermore, we found that older pickers were generally less productive with Pick by Voice. For Pick to Light we did not identify individual characteristics with a significant relationship to picking performance, suggesting that this picking tool is equally accessible to anyone.

Chapter 5. Safety Does Not Happen by Accident: Antecedents to a Safer Warehouse

The study presented in this chapter enriches the literature on safety-specific transformational leadership (SSTL) in two important ways. First, it establishes that a prevention focus of the warehouse manager serves as a determinant of SSTL. As already established by De Koster et al. (2011), we found that a higher level of SSTL relates to a lower number of warehouse accidents, even when controlling for a variety of hazard-reducing systems. A mediation analysis revealed that SSTL mediates the relationship between a prevention focus and accidents by explaining 71% of the variance in warehouse accidents accounted for by a prevention focus. Second, we did not identify a relationship between SSTL and quality or productivity. This is surprising, since based on the literature we expected that the increased focus on details of the work induced by SSTL would relate to a lower level of productivity and a higher level of quality.

Chapter 6. Which Drivers Should Transport Your Cargo? Empirical Evidence from Long-Haul Transport

In chapter 6 we focused on long-haul road transport to examine the influence of individual characteristics in a different logistical context by studying the role of driver characteristics in predicting driving safety and productivity. A substantial number of studies have investigated the role of the driver in predicting safety in particular (e.g. Arthur and Graziano, 1996; Cellar et al., 2000; Elander et al., 1993; Lester, 1991). This study extends the existing literature by using a unique combination of objective data from the GPS and Enterprise Resource Planning systems and surveys. The results show that, contrary to what was hypothesized, more safety-conscious drivers were generally more productive, and more conscientious drivers displayed riskier driving behavior. Based on an additional Necessary Condition Analysis (Dul, 2015) we suggest that a certain minimum level of safety consciousness is required for drivers to reach the highest levels of productivity.

7.2 Theoretical and practical implications

Even though behavioral operations is now considered as a well-established sub-discipline of operations management (Croson et al., 2013), the field is rapidly developing and still features various scarcely explored research avenues. This dissertation as a whole contributes to the theory and practice of operations management by focusing on some of these under-researched areas through the application of behavioral insights to novel operational settings and through the use of innovative methodologies.

Theoretical Implications

In this section we present some of the most important overarching theoretical insights obtained through the research performed as part of this dissertation. Besides the theoretical contributions to behavioral constructs such as regulatory focus and personality, we would also like to emphasize some methodological insights about the importance of employing behavioral experiments in operations management research.

The use of behavioral experiments in operations management. Twenty years ago, several researchers called for an increase of hypothesis testing and the building of theory in logistics and supply chain research. They argued that theory development was required to achieve growth as an academic field, but also to increase the generalizability to practice (Dunn et al., 1994; Mentzer and Kahn, 1995). The discipline of behavioral operations management has partly answered this call by employing behavioral insights to enrich and extend existing models and theories, and by obtaining empirical results to validate these novel ideas. Initially, the majority of empirical research in the field employed surveys and interviews to measure the latent behavioral constructs that are relevant for research in the context of operations (Dunn et al., 1994). The use of behavioral laboratory experiments in this context has been relatively scarce (Mentzer and Flint, 1997). Especially this type of experiments, which enable the isolation the cause-and-effect relationships of interest and commonly offer a high degree of control, can be highly valuable for building, extending, and testing theory (Tokar, 2010). Several studies demonstrate the potential of successfully using experiments to enrich theories in operations management by incorporating behavioral factors. Examples are the role of decision bias in the newsvendor problem (Becker-Peth et al., 2013; Schweitzer and Cachon, 2000), the influence of social preferences on supply chain transactions (Loch and Wu, 2008), and the effects of judgment errors in revenue management (Bendoly, 2013, 2011). A commonality between these studies is the focus on decision-making aspects or economics rather than on a pure operations context.

Chapters 2, 3, and 4 of this dissertation extend the existing literature by employing a rigorous experimental approach to the operational task of order picking. Such an approach is challenging, because a high degree of experimental control is difficult to achieve in most operational settings. However, we propose that controlled experiments such as the ones presented in this dissertation are necessary to achieve a combination of scientific rigor and results that are likely to generalize to operations practice. Such rigor does not only apply to a high degree of control over the experimental design, but also to a critical evaluation of the population of participants. Whereas students might be suitable participants in tasks focusing on operational decision-making (Thomas, 2011), they might be a less accurate representation of the target population in other tasks. Especially in the context of operations, frequently characterized by repetitive blue-collar work, it is important to carefully consider whether experimental results obtained in a population of students can reasonably be expected to hold in practice. Chapters 2 and 4 showed that professional workers perform differently than vocational students and academic students, and in the analyses we controlled for these differences to increase the validity of the findings. Together chapters 2, 3, and 4 demonstrate that the performance of an order picking process depends on a combination of the order picking method, the individuals working with the method, and the incentive system used to motivate these individuals. This does not only contribute to the literature on order picking, but is also of interest to the research on regulatory focus and incentive systems.

Regulatory focus. Because of its close link with performance, the role of regulatory focus has been studied in a variety of work-related contexts (Brockner and Higgins, 2001; Lanaj et al., 2012; Wallace et al., 2009). Also the interaction between regulatory focus and incentive systems has been examined (Shah et al., 1998). However, the study of the role of regulatory focus in a realistic task context that emphasizes physical labor more than mental exercise and decision-making is novel. Furthermore, the role of regulatory focus as a determinant of a specific safety-oriented leadership style presented in chapter 5 extends the existing research on the role of regulatory focus in leadership (e.g. Kark and Van Dijk, 2007; Kark, 2013; Stam et al., 2010) by emphasizing the mechanism through which leaders influence their followers.

Personality. Similar to regulatory focus, a number of studies and meta-analyses have demonstrated the relationship between personality, particularly the Big Five personality traits, and work-related behaviors and outcomes (e.g. Barrick and Mount, 1991; Barrick et al., 2001; Bono and Judge, 2004). Chapter 4 contributes to this rich base of existing literature by exploring the role of personality in a realistic controlled setting with various tasks that accurately represent a real operational labor environment. The role of driver personality in predicting safe driving, as investigated in chapter 6, has also been investigated in various other studies (e.g. Jones and Foreman, 1985; Oltedal and Rundmo, 2006). Chapter 6 contributes to these studies in two important ways. First, besides the relationship between driver personality and safety behavior, this chapter studies the relationship between driver personality and productivity. Second, the study makes use of a novel approach that combines data of multiple sources, preventing the common-method bias that is frequently an issue for studies on this topic.

Practical Implications

The choice for the research context and methodological approach of this dissertation have been strongly motivated by the desire to obtain results that are not only valuable in the development and testing of theory, but also applicable and useful in practice. In this section, we translate some of the results of the chapters in this dissertation to practical insights that can be used by managers.

Training and selection of managers to foster safety. In chapter 5 we found that more prevention-focused managers displayed more safety-specific transformational leadership, which in turn relates to a lower number of warehouse accidents without adversely impacting productivity or quality. In warehouses led by a manager with a relatively low prevention focus the number of accidents was approximately twice as high as in warehouses led by a manager with a relatively high prevention focus. This result suggests that companies operating in an accident-prone environment should try to make sure a prevention-focused manager is in charge. Achieving this can be done by employing prevention focus as one of the selection criteria in the hiring procedure for a new manager, and also through training and situational cues. Several studies have shown that the regulatory focus of an individual can at least to a certain extent be influenced (Förster et al., 1998; Higgins and Tykocinski, 1992). Companies could try to evoke a prevention focus in managers by emphasizing the avoidance of negative consequences in the vision and objectives of the company and potentially in the reward system. Some concrete impact has already been realized: Our findings have triggered the organization of the annual Dutch election of the safest warehouse to include the prevention focus and safety-specific transformational leadership of the warehouse manager as additional assessment criteria.

Aligning employees with tasks and incentive systems for performance. Companies use incentive systems to increase performance, but in chapters 2 and 3 we found that not all incentive systems are equally effective for all types of tasks and for all types of individuals. This finding suggests that it is unlikely that company-wide incentive systems that generalize across all tasks and positions are optimal. Instead, companies could consider the implementation of different incentive systems depending on the characteristics of the tasks (e.g. the degree of independence/interdependence) that have to be executed. Furthermore, once a company aims to hire personnel to work on a specific task with a particular incentive system, individual differences such as regulatory focus can be measured using surveys and considered in the hiring process to more accurately predict future job performance. The results of chapter 2 suggest that the impact of aligning individuals with incentive systems and picking methods can yield productivity gains of up to 40%.

Selecting and training of drivers for safety and productivity. The results of chapter 6 suggest that individual differences between drivers explain part of the variance in productivity and unsafe driving behavior. For example, drivers scoring relatively high on safety consciousness drove on average 7.5 km/h faster than drivers with a relatively low score on safety consciousness. This knowledge can be beneficial for trucking companies by providing insights into which of the existing drivers might need additional safety training and into which new drivers should be hired. Personality tests and questionnaires on safety consciousness can be used to achieve this. The finding that more conscientious drivers displayed more dangerous driving behavior suggests that their main goal was to be productive. Trucking companies should therefore also ensure that the objective is not only to be productive; safe driving should also always be emphasized and, if possible, rewarded.

7.3 Strengths, limitations, and future research

The five studies presented in this dissertation provide an insight of the impact of behavioral factors on the outcomes of several logistical processes and through the use of multiple different methodologies. However, like all studies, this dissertation is also subject to certain limitations. These limitations might, to a certain extent, influence the interpretation of the results, but could also offer avenues to extend the current research. In this section we present several of these limitations.

Causality. Chapter 5 of this dissertation employed a cross-sectional study to provide evidence for the relationship between a prevention focus of the warehouse manager, safety-specific transformational leadership, and warehouse accidents. Even though we believe that there are sufficient theoretical grounds to expect that the direction of the identified relationship is in line with our hypotheses, the methodology does not provide the opportunity to properly establish causality. In order to establish that the manager is responsible for creating a safe warehouse and to eliminate the possibility that the effect can purely be explained by safer warehouses hiring more safety-oriented managers, panel data obtained through measurements at multiple points in time would be required. Gathering such data is a difficult process because of the high turnover rates of management and personnel, but remains an important task that should be executed in the near future.

Student participants. In chapters 2 and 4 we included professional order pickers in the group of participants to the experiments to increase generalizability of the results. This is an obvious strength of these studies, as the differences in results between professional pickers and students demonstrated that it is not always possible to assume results obtained with student participants generalize to operations practice. However, this finding also exposes a potential weakness: In chapters 2 and 4 we also employ student participants, and the experiment in chapter 3 even exclusively relies on students as participants. We believe that if professionals would also have participated to chapter 3 in this dissertation the conclusions would not be radically different, but future behavioral studies in operations management should seriously consider including professionals in the participant pool.

Chronic and situational regulatory focus. In the studies presented in chapters 3, 5, and 6 we included regulatory focus as a chronic, dispositional construct that remains stable within individuals. The assumption that regulatory focus consists of a chronic component has been confirmed in other studies. However, in addition to this chronic component, regulatory focus is thought to consist of a component that can be changed in response to environmental stimuli (Förster et al., 1998; Higgins and Tykocinski, 1992). This environmental component could be included as part of future studies. For example, in the order picking experiment of chapter 2 we could measure whether the regulatory focus of participants changes as response to different incentive systems, potentially explaining some of the identified effects. Similarly, it would be interesting to find out whether the identified effects of safety leadership on warehouse accidents of chapter 5 occur through an influence of the leader on the regulatory focus of warehouse employees.

Outcome measures. This dissertation studies the role of behavioral factors in various operational processes, but these behavioral factors are mostly studied in the role as predictor of the 'classic' operational outcomes productivity and quality. It is important to realize that behavioral operations is broader than this focus on inputs, and that more human outcome factors can be investigated as well. For example, in chapters 4 and 5 we did this by focusing on safety as outcome variable. However, especially chapters 2, 3, and 4 could benefit from incorporating more outcome measures that focus on the operators of the investigated processes, such as discomfort, stress, fatigue, physical and mental strain, job satisfaction, and boredom resulting from the work they perform. Investigating these outcomes could provide insight in potential tradeoffs, interactions, and complementarities between traditional measures of performance and human outcomes. Realizing this will most likely require a different research setup as many of these human outcomes are not directly influenced by short-term manipulations, but rather the result of performing a certain task for an extended period of time.

Implications without replication. In several chapters of this dissertation we have provided specific recommendations that organizations and managers can employ to improve several aspects of performance. The findings presented in these chapters provide support for these recommendations, but it is important to realize that all samples can be subject to biases that influence the outcomes of the studies. Therefore, replications are necessary to establish that the conclusions also hold in different contexts with different samples, and that the findings are not just statistical artifacts.

Limitations of PLS-SEM and NHST. In chapter 5 partial least squares structural equation modeling (PLS-SEM) is used to test our hypotheses. The use of structural equation modeling in OM is widespread (Shah and Goldstein, 2006). Initially structural equation modeling was limited to covariance-based (CB) SEM, but more recently PLS-SEM has seen a growing number of applications in OM as well (Peng and Lai, 2012). Especially the use of PLS-SEM has been subject to debate and criticism (e.g. Goodhue et al., 2012; Marcoulides et al., 2012; Ringle et al., 2012). Most of the criticism focuses on the fact that PLS-SEM can be subject to biased parameter estimates (Peng and Lai, 2012), has often been applied wrongly to inappropriate data situations, and is frequently used as method to overcome the problem of insufficient sample sizes (Hair et al., 2011). According to Hair et al. (2013) PLS-SEM can be an appropriate method if researchers are transparent about the sampling technique and sample, carefully state the goal of the analysis, and comprehensively report and evaluate the results. These same criteria also largely apply to null hypothesis significance testing (NHST), one of the most commonly employed tools to evaluate hypotheses. Also in this dissertation we have used NHST extensively, and we believe that methods such as NHST and PLS-SEM are subject to several limitations and arbitrary decisions (Nickerson, 2000). However, to at least partly address this issue, we have consistently focused on multiple criteria beyond significance. Examples are the actual impact size of our findings and the necessary condition analysis (NCA) employed in chapter 6. Methods such as NCA could also be applied to the other chapters to discover necessary conditions. For instance, in chapter 5 it would be interesting to find out whether a minimum level of safety-specific transformational leadership is required to run a warehouse with low accident rates.

Non-significant results. Throughout this dissertation we have discovered several statistically significant relationships, but we have also identified predictors that did not significantly predict the investigated outcome variables. Even though this absence of an identified relationship was surprising in certain cases (e.g. SSTL did not significantly predict quality or productivity), we have to remain very careful in employing these results to formulate predictions. The identified absence of a statistical relationship does not indicate that this relationship is non-existent, but simply that we did not identify it. To draw more thorough conclusions about these results it is be necessary to more closely investigate the confidence intervals and operationalizations of our variables.

Long-term effects. Chapters 2, 3, and 4 use data obtained from an experiment to assess the influence of multiple factors on productivity and quality. Even though in chapter 3 we attempted to increase the generalizability of the results by investigating a task with a longer duration, the duration of the experiments was still relatively short compared to the time people execute the investigated tasks as part of their daily job. As also stated in these particular chapters, it is therefore not clear to what extent the identified effects generalize to the long-term. It could be the case that on the longer term, motivation caused by the alignment of incentives and tasks wears off. Furthermore, as extensively described by Martinelli (2010), the additional effort required to reach higher performance could also lead to several negative side-effects on the longer-term, such as an accumulation of fatigue, chronic discomfort, and physical health problems such as lower back pain or Repetitive Strain Injury. Paying attention to these potentially negative side-effects is important when implementing the findings of these studies in practice.

Generalizability of the research context. The research that makes up this dissertation is performed in and focused on rather specific environments: warehouses and long-haul road transport. However, we expect that most of the obtained results and conclusions generalize beyond these contexts. For example, the task of order picking does not differ considerably from other types of repetitive labor or simple production work and the findings about safety in warehouses could potentially generalize to other types of facilities such as production plants. Similarly, the research context of long-haul road transport in India could very well generalize to other settings characterized by chaotic and frequently unpredictable traffic situations. Examining whether the results indeed hold in related settings could be an interesting opportunity for future research, as it could drastically increase the impact of the presented studies.

7.4 Concluding remark

This dissertation aimed to obtain more insight into the influence of several behavioral aspects and individual differences in the context of logistics. We found that the outcomes of multiple different logistical processes can to a certain extent be explained by taking individual differences and behavioral aspects into account. These insights offer numerous opportunities to improve and refine existing models in operations management. Furthermore, I hope that our use of novel methodologies such as experiments in operational settings will inspire other researchers in the field of (behavioral) operations management in their research endeavors. I believe this should not only improve the richness of the operations management literature, but also greatly helps to bridge the gap with practice. After all, individual differences make a difference.

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Summary

In the world of logistics, a considerable share of all work is automated and performed by machines or robots. An examination of the existing logistics research reflects this image, since a substantial share of the studies focus on automated processes, and perfectly predictable systems. This is however not the whole picture. People play an essential role in almost every node in a supply chain as well, and when human behavior is involved things become less predictable. The roles of people in supply chains range from more managerial tasks such as decision-making to operational tasks such as order picking and driving. Especially the role of human behavior in this latter category of operational tasks is an under-researched topic. This dissertation aims to contribute to theory and practice by investigating exactly this issue: which behavioral factors and individual characteristics of people influence the outcomes of logistical processes, and to what extent? This question is addressed in five chapters, each of which focuses on different individual characteristics, a different research context, or a different methodological approach.

In chapters 2, 3, and 4, we used behavioral (field) experiments to investigate the performance of different order picking tools, systems, and incentive systems. Furthermore, we examined the role of picker personality and regulatory focus, a mindset that influences how people perceive goals and act, in this context. The result show it is important consider individual differences when determining which people to deploy in a particular task and how to motivate them. Doing so can result in a substantial increase in performance and corresponding reduction of wage costs.

In chapter 5 we study the relationship between safety-specific transformational leadership (SSTL), a leadership style geared towards fostering safety, on warehouse accidents, and the determinants of this leadership style. We show that prevention-focused leaders are more likely to display SSTL, which in turn relates to a lower number of accidents.

This result can help companies to select and train the right manager to foster safety in their warehouse.

In chapter 6 we investigated the role of individual characteristics of truck drivers in predicting driving performance in terms of safe driving behavior and productivity. Several personality traits significantly influenced performance. For example, more conscientious drivers displayed more dangerous driving behavior. Furthermore, the results suggest that a certain minimum level of safety conscious is necessary for truck drivers to reach top levels of productivity. The productivity difference between drivers scoring high and drivers scoring low on safety consciousness was approximately 7.5%, translating to time savings of about 3 hours on the average trip in our sample.

As a whole, this dissertation aimed to obtain more insight into the influence of several behavioral aspects and individual differences in the context of logistics. We found that the consideration of individual differences and behavioral aspects helps to more accurately explain and predict the outcomes of multiple different logistical processes and outcomes. These insights offers numerous opportunities to improve and refine existing models in operations management.

Nederlandse Samenvatting (Summary in Dutch)

Over het algemeen is het beeld van de logistieke sector, en magazijnen in het bijzonder, dat het werk grotendeels geautomatiseerd of gerobotiseerd wordt uitgevoerd. Dit is deels waar, maar de realiteit is ook dat mensen een essentiële rol spelen in bijna elke stap van productie- en distributieketens. Het gedrag van mensen is vaak onvoorspelbaar en soms irrationeel, waardoor processen en uitkomsten beïnvloed kunnen worden. Toch richt traditioneel gezien een groot deel van het onderzoek op het gebied van Operations Management zich voornamelijk op het modelleren en analyseren van perfect voorspelbare processen. Tegenwoordig bestaat er echter ook onderzoek dat zich richt op de rol van mensen en gedragskundige factoren binnen logistieke processen. Meer inzicht in de rol van dergelijke gedragskundige factoren kan een helpen bij het verbeteren van bedrijfsuitkomsten als productiviteit, kwaliteit, en veiligheid. Dit proefschrift draagt hieraan bij door te kijken naar de invloed van zowel interne als externe gedragskundige factoren op meerdere soorten uitkomsten in diverse logistieke processen.

In hoofdstuk 2 onderzoeken we de invloed van de manager op veiligheid in magazijnen en bekijken we van welke managers meer veiligheidsspecifiek leiderschap verwacht kan worden. In hoofdstuk 3, 4 en 5 richten we ons op de context van order picking en tonen we aan dat interne factoren zoals regulatory focus van orderpickers en externe factoren zoals de beloningsstructuur en pickmethode beiden prestaties beïnvloeden. Hoofdstuk 6 biedt inzicht in de invloed van persoonlijke kenmerken van vrachtwagenchauffeurs op onveilig rijgedrag en productiviteit. Hierbij suggereren de bevindingen dat veiligheidsbewuste chauffeurs over het algemeen minder productief zijn

(zonder onveiliger te rijden) en dat consciëntieuze chauffeurs meer onveilig rijgedrag vertonen (zonder productiever te zijn).

Als geheel tonen de inzichten verkregen door middel van het onderzoek in dit proefschrift aan dat gedragskundige factoren een belangrijke rol spelen binnen verschillende logistieke processen en uitkomsten, en dat het in beschouwing nemen van deze inzichten zowel theoretisch als praktisch zeer waardevol kan zijn.

About the Author

Jelle de Vries (1988) received his bachelor's degree with majors in Economics and Psychology and a minor in Statistics from University College Utrecht in 2010 and graduated from the ERIM MPhil Research Master program at Rotterdam School of Management (RSM), Erasmus University in 2012. His master thesis, focusing on the impact of leadership on warehouse safety, won the Dutch Logistics Master Thesis Award. After his graduation, he continued working at RSM to pursue a PhD degree. His research interests include behavioral operations management, warehousing, and occupational safety. In early 2015, he was a visiting scholar in California at the Naval Postgraduate School in Monterey, and California Polytechnic State University in San Luis Obispo. His research findings have been presented at various international conferences including POMS, AOM, ILS, and LOGMS. In the fall of 2015, he started his tenure track at VU University Amsterdam.

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BEHAVIORAL OPERATIONS IN LOGISTICS

People play an essential role in almost all logistical processes, and have a substantial influence on logistical outcomes. However, in their actions and decisions people do not always behave perfectly rational. This can be problematic, especially as most processes and models do not take this potential irrationality into account. As a consequence, theoretical models are often less accurate than they could be and companies might be confronted with suboptimal outcomes. The field of behavioral operations aims to address this issue by departing from the assumption that all agents participating in operating systems or processes are fully rational in not only their decisions, but also in their actions. This dissertation focuses on addressing the latter aspect by investigating which behavioral factors and individual characteristics of people influence different outcomes in (intra)logistics, and to what extent. In five separate studies, we consider not only productivity as outcome measure, but also safety and productivity. More specifically, we study the relation between these outcomes and behavioral factors such as regulatory focus, personality, safety-specific transformational leadership, and incentive systems. The results provide a strong illustration of the potential impact of behavioral factors in the (intra)logistical context, and can help managers to increase safety and productivity in their organizations.

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