ELFRIEDE IRENE KRAUTH

Real-time Planning Support

A Task-Technology Fit Perspective

Real-time Planning Support

a task-technology fit perspective

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a task-technology fit perspective

Real-time Planningsondersteuning
de afstemming tussen taak en technologie

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Preface

Waves are energy that travels for maybe several thousands of kilometers before it hits a beach and rises to the surface where it becomes visible as a wave. The process of catching waves includes first paddling three or four strong strokes towards the beach to have a high speed when the energy of the wave pushes the board. This energy gives the board the necessary stability so that the surfer can stand up and surf. Deciding to paddle in order to catch the wave when and where it has the most energy proves to be very difficult. However, surfers that try to catch every wave will quickly run out of energy and may not even catch any waves at all. Surfing requires good qualities in real-time decision making.

Transport planning is in some aspects not unlike surfing. Logistics is about delivering the right product in the right quantity, at the right place and at the right time. Clients want to place or change their transport orders increasingly at the last minute. The unpredictable and volatile demand gives planners little time to adjust plans and ensure high efficiency. While there are decision support systems available for calculating the shortest transport route or the optimal order-resource assignment, we know little about how to give this advice in the chaos and unpredictability that characterize the decision making situation in real-time transport. Planners may make decisions in a manner different from decision support systems. They may be subject to manipulation depending on the way data are presented. There might even be a mismatch of how developers expect planners to use the decision support systems - and how they are actually used in practice. Factors such as time pressure and the organizational structure may further influence information processing capabilities of individual planners.

This dissertation wants to explain planning performance as a function of deliberative decision making shaped and limited by an interplay of cognitive resources, situational factors and technology. The research objective of the dissertation is to investigate mechanisms of fit between the planning task and planning technology in a real-time transport context. From an academic perspective, this dissertation contributes to the field of Behavioral Operations Management. The practical implications of this dissertation are of interest mainly for managers of transport and transport software companies.

Performance is one of the aspects in which logistics and surfing do differ: catching demand in transport may be the difference between staying in business or not; catching a wave in surfing may be the difference between riding the energy that travels the oceans or just another nice day at the beach.

Acknowledgements

Rotterdam has given me, what I have came here to do: write a PhD in LaTeX. However, the road till sending this book to the printer in many ways resembled the "Road to Ithaca", a poem of Cavafy (1911): "wish that the way be long, full of adventures, full of experience, [...] and when finally [...], you berth on the island, [you know that] ... Ithaca gave you this lovely voyage." Well, my PhD journey has given me this book and I am happy to acknowledge the people that have made the journey possible and worthwhile, here, in the one section of the book that for most people will be the only one they read.

As suggested by Cavafy, I was learning from the studious, and this in the first place includes my promotors, Prof.dr. Steef van de Velde and Prof.dr. Jos van Hillegersberg. I have been very lucky in this regard. Steef has been my first promotor and daily supervisor. Steef as you mentioned in our first discussion here at RSM, German PhD students indeed are inclined to do whatever their bosses suggest. You also said I may hurt your feelings once in a while. Thank you for this most kind offer (how often did I make use of it?) and the many other ways and instances in which you encouraged me to go my own way. Steef, you have this rare combination of being very precise in your comments, holding up high standards, yet at the same time creating an environment for my PhD that can be best described as chilled with plenty of confidence that a better version is out there and completely within reach. If this book is kort and krachtig, then because of you.

Roughly speaking, I studied the use of OR algorithms embedded in Information Systems. For this Steef and Jos make the perfect support team, as the OR perspective was covered by Steef, and the perspective of Information Systems by Jos, my second promotor. Jos thank you for the critical remarks during the various stages of this project, introducing me to your network and the best advice on presenting I ever got: "you're in the Dutch team now, you have to add some pictures".

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Cavafy further recommends the traveler to "enter harbors never before seen [... to] stop at Phoenician stalls [and] go to many Egyptian cities." The generous support of ERIM has made it possible for me to do so, at least in the figurative sense. But ERIM not only provides financial support. I want to thank Tineke van der Vhee and Olga Novikova for their encouragement and the nice chats in the past years.

During my PhD I stayed at the Helsinki University of Technology (HUT), Finland working together with Prof.dr. Jan Holmström. Jan, I want to thank you for your hospitality and your refreshing perspective on the field. Also, I want to thank NWO, the Trustfonds of the Erasmus University and ERIM for their financial support of this research visit.

On the first encounter some of the "surprising" results presented in this dissertation resembled "the Laestrygones and the Cyclops and the angry Poseidon" described by Cavafy. The frustation before the arrival of the liberating insight was usually just as huge as the relief afterwards. Both stories I just needed to share and I am grateful for everyone who welcomed me to do so. This especially includes my to paranimfem, Cokky Hilhorst and my brother Axel Krauth. Above all, you were the ones most frequently giving me the change in perspective when all I could see was an angry Poseidon. Thank you Cokky, for your friendship, your compassion, a truly great sense of humor, and being the the listening ear for all the trials and fun life has to offer inside and outside of research. Axel, let me put it like this: Who would have thought that the largest source of irritation when I was nine would turn out to be the complete opposite some twenty years later during my PhD?

In addition, I want to thank Dr. Hans Quak and Hans Moonen for being the masters of ceremony not just on the day of the defense but during my whole stay in Rotterdam. I very much enjoyed our conversations on various topics which I feel free to summarize as: agonizing over agents, revealing the meaning of a research question, and always: loving logistics. But also, van harte bedankt voor introducing me to the art of conferencing, how to kill and stay alive during Mafia, and just generally how to be happy as a Hans in Holland.

A PhD may start on a certain date, but the people you have met on the way leading up to it are part of the support you lean on while doing it. Ein herzliches Dankeschön an Daniela Dotterweich und die wunderbare Stammbelegschaft vom Zuck: Antje Sonnenschein Blumenauer, Ursula Cimiano, Markus Hochholdinger, Björn Holst und Andrea Kexel. Muchas gracias a María López Gonzalo. Although we see each other less often than we used to, we manage to stay close in other ways and it is still so easy to reconnect. It gives me a lot of comfort that I am always just one text message away from that. I so much enjoy your visits, your hospitality at short notice, your sharing of stories and listing to mine. I am glad for the times we had, and look forward to the ones yet to come.

This journey would have been a lot less fun were it not for the colleagues from department 6, the lunches, the seminars, the strategy days. Department 6 provides a very friendly, open and non-hierarchical environment. And for foreign PhD candidates it is also the place they are introduced to many Dutch habits and traditions, my favorite one being Sinterklaas. It was such a pleasant surprise to celebrate ”Christmas” in a completely non-commercial manner, focusing on gezelligheid, the writing of page long poems to each other, and singing. I especially enjoy the choreography that goes along with ”Dag Sinterklaas”.

Some special people I want to mention from department 6: Dr. Mengfei Yu, a very dear thank you for the companionship, sharing of the nice and the not so nice aspects about living in the Netherlands and conducting a PhD. I am particularly indebted for you pointing out the similarities between surfing and logistics. Oh, and: ni hen piao liang, dan ni hen wen jou. Irma Borst, who boldly went where she did not want to go: the realm of over-dispersed models. Thank you for sharing the wisdom you brought back from that trip, being such a role model and so much fun to be around. Jordan Srour, DNA with PNA, thank you for all the editing during the years, reliably making me feel good about my research and just genuinely being a good friend. I'm looking forward to catching up with you again, whereever that may be. I cannot leave Dr. Serge Rijsdijk unmentioned, who I would turn to when I was stuck in statistics. Thank you, Serge for providing frequent support and especially doing that in such a kind way. And, of course, Carmen Meesters. Van harte bedankt for the administrative support, the sincere encouragement and the firm conviction: het komt wel goed!

Apart from the university I found a very special group of women with whom to share the working life of a female thirty something (well not all of you are there yet, just wait :-)). Learning tennis was one of the best decisions I made in Rotterdam. Spending a whole Saturday playing and watching tennis, and talking not only about tennis, has proven to be a very efficient way to get my mind off of research. It is also a very fun one. Thank you for the gezelligheid on and off the court: Claudia Middelkoop, Tine Niezink, Rinske Verwaal, Heleen Westerman, Petra de Wit. In addition, Rinske, thank you for translating my German summary to Dutch. It is just great being able to completely outsource such a task, especially in the times of the laatste loodjes.

There are many ways in which I received support during the last years. And often a listening ear, an understanding nod, and let's not forget the flauwe grap were a much appreciated gesture. However, my ”stay” in Rotterdam and the finishing of this dissertation would not have been possible without some more demanding support. Thank you for the proofreading as well as the moving of my stuff from one house to the other: Niels Agatz, Dr. Henri Burgers, Dirk Deichmann, Bart van Hezewijk, Cokky Hilhorst, José Larco Martinelli, Hans Moonen, Dr. Hans Quak, Dr. Serge Rijsdijk, Jordan Srour, Bas Verheijen, Rinske Verwaal, Dr. Mengfei Yu. The fact that some of you belong to both categories, shows just how applied research at RSM can be and how you don't shy away from strenuous labor. However, the icing on the moving cake are Rinske Verwaal and Hans Moonen, who let me stay in their apartment for a few months as if it was the most natural gesture of all.

Last but not least I want to thank my parents. You have not always been in favor of the steps I have taken but always provided your support anyway. Actually, it is difficult to find the right words and the courage to write them down to express how I feel about you and all that I am thankful for. All I can muster up is this: I'm so glad to have you.

As I finish this book or, in the words of Cavafy, as I am close to berthing on the island, this journey is coming to an end. I am looking forward to the ones ahead.

Elfriede Krauth
Rotterdam, November 2008

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Chapter 1

Introduction

1.1 The task of planners in transport companies

The research objective of this dissertation is to investigate mechanisms of fit between the planning task and planning technology in a real-time transport context. From an academic perspective, this dissertation mainly contributes to the field of Behavioral Operations Management (Bendoly et al., 2006; Loch and Wu, 2007). The practical implications of this dissertation are of interest mainly for managers of transport and transport software companies.

Data from the Netherlands, one of the most important logistics countries in the European Union, illustrate the importance of the planning task in transport companies. Planners directly influence gasoline and labor expenses, which account for more than 60% of the total costs in Dutch transport companies (NIWO, 2008). Next to the transport companies themselves, the general public has an interest in high efficiency of transport. The transport industry is responsible for one third of the CO_2 emissions caused by passenger and freight road traffic which is one the major sources of pollution in the European Union (Malgieri et al., 2007). The potential for increasing efficiency is still enormous: in 2007, on average, Dutch trucks were traveling empty for more than 25% of the distance (NIWO, 2008).

The task of planners in transport companies may include several responsibilities (summarized in Table 1.1). Based on known orders or forecasts orders, planners can combine loads from several customers and then determine pick up and delivery time. Planners may also consider and handle subcontracting of loads to other transport com-

Table 1.1: Decisions in various phases of the planning process in transport companies

Phases in the transport process	*Identified decisions and consequences for the planning task*
Before execution	
Order receipt	Customers may vary regarding they level of detail of their orders, how early they place orders and how frequently they change them. Planners may also have to carry out price negotiations.
Load planning	Consolidation of less than truckload (LTL) to full truckloads (FTL). Scheduling of pick up times and delivery time and communicating them to customers.
Fulfillment plan	Deciding if some orders should be subcontracted to other companies and the handling thereof. Order-truck assignment for own trucks.
Storage design and trip planning	Finding optimal storage within container or truck. Vehicle routing
During execution	
Load pick up and delivery, event handling	Checking of execution status and of correct pick up and delivery. Handling of events such as changing customer demand or traffic.

Source: adapted from CapGemini (2005)

panies. In addition, planners may need to assign orders to trucks, decide on the storage within the truck or container and determine detailed route plans for drivers. In some cases, customers or drivers may take some of these decisions. During execution, planners may check status and handle events caused by changing customer demand or problems arising from truck failure or traffic jams. Financial settlement typically takes place after order execution and is not necessarily done by planners.

On an abstract level, planners may carry out the same or similar decisions. However, their actual tasks and the way they are carried out can vary. For example, some planners may subcontract orders to other companies more often than other planners. The extent to which carrying out a task depends on information exchange with others is referred to as *interdependence* (Thompson, 1967; Aiken and Hage, 1968; Wybo and Goodhue, 1995). We define the extent to which carrying out the planning task depends on information exchange with planners from the same or from other companies as *planner-interdependence*. Planners can also differ in how they find solutions to planning problems. Some planners may determine the shortest route for visiting a given set of cities by calculating all possibilities and then selecting the best. Other planners my simply examine the cities as they are laid out on a map and find the shortest route based on geometric properties (Applegate et al., 2007). The first approach will guarantee the shortest route, but it is also more time consuming and cumbersome. The second approach typically costs less effort. Based on existing literature, we define *planning effort* as the complexity of the search process and cognitive processing carried out by planners as they perform the planning task, prevent or recover errors (Perrow, 1967; Price and Mueller, 1986; Jackson et al., 1993; Wall et al., 1995). We choose to call this construct planning effort instead of planning difficulty since cognitive processing in a planning task is not only a reflection of the task itself but also of the choices planners make in how to carry it out. Next to effort, problem solving approaches may differ in the extent to which they are abstract. *Cognitive style* refers to the way people make decisions (Witkin et al., 1971; Van Bruggen et al., 1998; Banker and Kauffman, 2004). Decision makers with a high-analytical cognitive style are more likely to solve problems in an abstract manner, while decision makers with a low-analytical cognitive style are more likely to solve problems within the given context. Also, *time pressure* can influence the process and quality of decision making (Hwang, 1994). Performance of planners can be measured by objective solution quality including aspects such as efficiency and service of the executed transport. In order to capture not only the objective solution quality of decisions but also the speed with which planners carry them out we adapt the concept of decision satisfaction to the transport planning context (Sanders and Courtney, 1985 and Lilien et al., 2004). We define *planning satisfaction* as the satisfaction with decisions of planning department.

The problems that planners need to solve often do not only have a large solution space, but are also intrinsically very hard to solve to optimality or near-optimality, even with the most sophisticated algorithms. Take for instance the archetypical problem of finding the shortest route through a given set of cities, which is commonly referred to as the traveling salesman problem (Applegate et al., 2007). Even the fastest computers can not be guaranteed to solve a traveling salesman problem of more than 75 to 80 cities to optimality within reasonable time (Toth and Vigo, 2002). In principle, planners may solve their problems in a rational way, which typically implies evaluating all possibilities and then selecting the best (Simon, 1955). However, decision makers do not always have necessary computation and time to examine all solutions, and their problems and preferences may not be well-defined enough for easily favoring one choice over another. The concept of *bounded rationality* acknowledges the constraints that decision makers encounter in a realistic setting (Simon, 1955).

As a way to improve their services, transport companies may allow customers to place orders late and change them shortly before or even during execution. We refer to such an environment as a *real-time transport context*. In such a context, frequent customer interruptions, time pressure and low reliability of data that enters decision making put additional strain on the planning task (Mills and Moberg, 1982; Frei, 2006). Under time pressure planners are more likely to resort to less thorough ways of decision making with possibly negative implications for objective solution quality (Maule and Svenson, 1993).

1.2 Technology: Agent-based decision support systems

Decision support systems (DSS) are computerized information systems (Eom, 2003; Power, 2008). For example, very basic DSS are text files which display all the orders for one day. By using such an overview, the planner does not need to keep all the order information in his working memory; instead he can concentrate on more difficult aspects (Baddely, 1992; Lerch and Harter, 2001). DSS can also carry out calculations for the user by incorporating mathematical principles and procedures developed in the field of Operations Research (OR). We define *OR-based DSS* as decision support systems that support planners in exploring the solution space using one or more Operations Research algorithms. Planning processes can benefit from OR-based DSS in terms of solution quality and speed of decision making. To stress the interactive nature of these systems, they are sometimes also referred to as *interactive planning systems* (Anthonisse et al., 1988). *Spatial DSS* can combine OR algorithms with geographical presentation of data (e.g. points on a map), and further provide information such as indicating pick up and delivery points (Crossland et al., 1995; Tarantilis and Kiranoudis, 2002).

In this dissertation, we focus on the use of DSS rather than the DSS itself. Therefore, we do not specify its technological features, and as a result the above definition of DSS is rather broad. Unless otherwise stated, a DSS is simply any kind of computerized information system used for operative planning purposes.

Next to finding the optimal solution and storing data, technology may also assist planners in collecting data. Satellite-based communication systems can deliver data on temperature of freight and motor, gasoline usage and labor hours in real-time to the planner (Rishel et al., 2003). Technologies that support *auto*matic *id*entification of products, pallets, containers or vehicles are sometimes referred to as Auto-ID technologies (McFarlane and Sheffi, 2003). Management of current location data for products is sometimes also referred to as tracking (for an overview and a distinction between tracking and tracing, view Kärkkäinen et al., 2004). Currently, Radio Frequency Identification (RFID) which enables monitoring of products, receives a lot of attention from academia and industry (Levans, 2004; Lee and Özer, 2007). Similarly to our conceptualization of DSS, we do not distinguish monitoring technology by its technological features but by its impact on the planning task. We define *sophisticated monitoring technologies* as systems that give planners real-time information on the status of trucks and orders. Tracking technology typically refers to the monitoring of products.

Agent technology can enable further functionality for DSS. Agents are small software entities that can analyze, observe, communicate, learn, and pursue goals (Wooldridge and Jennings, 1995). These skills are not new. However, before they were present mostly at the level of the application. For example, the application was able to search the internet. With agent technology, individual modules can start background searches. Apart from new approaches to problem solving, agent technology also enables new forms of human-computer labor division (Maes, 1994; Maglio and Campbell, 2003; Nissen and Sengupta, 2006). For the real-time transport context, two functionalities provided by agent technology might be especially useful:

Monitoring Agents can monitor data streams generated by sophisticated monitoring technologies and combine them with traffic information gathered from the internet and historical data stored in the computer of the planner (Banker and Kauffman, 2004). This information can be used by OR-based algorithms to calculate the probability that a certain truck will for instance pick up a customer order in time. Agents can carry out this computation continuously, and only notify planners when a certain threshold is crossed. This notification may also include a recommendation on how to solve the problem.

Negotiation Agents can participate in auctions for transport orders held on the internet (Figliozzi et al., 2006; Lin et al., 2002). In order to calculate an auction bid, the agent might take real-time execution information and historical data into account. Agents can either close the deal themselves, or let the planner make the final decision to acquire or subcontract orders or resources. Agents can participate in several auctions simultaneously which may be difficult for the planner.

Electronic transport market places facilitate finding buyers and sellers of transport services (Goldsby and Eckert, 2003). With agent technology, transport companies reap some of the benefits of participating in online transport auctions, while cutting down the time that planners are involved in monitoring and initiating the process.

It is not necessary to use agent technology for the above mentioned features, and this dissertation does not participate in the discussion on the appropriateness of agent technology in a logistics context (Fischer et al., 1996; Davidsson et al., 2005; Mes et al., 2007; Mahr et al., 2008; Moonen, forthcoming). We see agent-technology is a paradigm that enables new forms of human-computer labor division. To summarize, the advent of interactive planning systems allowed human-computer labor division to evolve from "I solve the problem for you", to "I can help you explore the solution space" (Anthonisse et al., 1988). Monitoring and negotiation functionality further change the nature of decision support, which can be paraphrased as: "I take care of time consuming monitoring and negotiation activities, and only ask you for intervention when I encounter predefined problems" (Nissen and Sengupta, 2006).

1.3 Task-technology fit

OR-based DSS can be useful for decision making as they can combine the accumulated knowledge of the OR community with computation capabilities that are superior to human handling in terms of calculation speed and accuracy (Blattberg and Hoch, 1990). Yet they are used to a low extent (Bendoly et al., 2006; Loch and Wu, 2007; Dietrich, 2007). Companies might lack financial resources to buy specific software (Golob and Regan, 2003). Further reasons for the low adoption rates may be that existing tools neglect certain aspects relevant to practice (Bendoly et al., 2006). In other words, the technology does not fit the task. There are various ways in which such a misfit can occur. For example, a company might find an off-the-shelf solution too general for its specific business problem (Golob and Regan, 2003). Further, the decision maker might not find the DSS adequate because it can never completely cover the real-world problem (Anthonisse et al., 1988). Planners may have knowledge on execution of a specific order or on customer demand that is difficult to communicate to the system (Hill, 1982; Powell et al., 2000). Decision makers tend to think that manual problem solving leads to better solution quality than heeding advice from a system they perceive as suboptimal (Davis and Kottemann, 1995). In addition, the effort of using a DSS may not always be outweighed by the perceived increase in solution quality (Payne, 1982; Singh and Singh, 1997).

While Operations Management tools and techniques can inform us what advice to give to planners, we apparently also need to know how to give it. This is not a question of replacing the human planner by the planning software but rather finding a way so that they complement each other. To create such a synergy, we first need to understand how planner and planning technology interact. The research objective of this dissertation is exactly this: to investigate mechanisms of fit between the planning task and planning software in a real-time transport context. Fit between task and technology is defined as the extent to which technology matches the requirements of the task and skill level of the user; high fit is presumed to increase performance (Goodhue, 1995; Goodhue and Thompson, 1995). The task-technology fit perspective not only includes cognitive information processing, but also broader aspects such as those related to data retrieval and bureaucracy. Task-technology fit examines the interaction between user and tool during the process for which the tool is intended or used. We refer to these interaction patterns as mechanisms. Mechanisms of fit are then theories that can explain why some interaction patterns outperform others.

Achieving a fit between task and technology is not straightforward, as planner and planning software may have different ways of solving the same problem (Hill, 1982; Applegate et al., 2007). Planner and planning software differ not only in how they solve the same problem, but also in the unique skills and benefits they bring to the planning process. Planners typically contribute creative problem solving and diagnosis skills, whereas planning technology typically provides quick and less error prone computation (Blattberg and Hoch, 1990). Planners can contribute customer care and negotiation experience, whereas planning technology can provide fast exchange of large quantities of data (Van Wezel and Jorna, 1999; Ahmad and Schroeder, 2001). The traditional interaction between the planner and the decision support system, in which planners run models with several different input variables (Anthonisse et al., 1988), may be too time consuming in a real-time transport context, and does little justice to the many possibilities of representing information and influencing decision making offered by modern graphic packages and the decision support functionality provided by agent technology (Maes, 1994; Rhodes and Maes, 2000; Lurie and Mason, 2007).

1.4 Behavioral Operations Management

Compared to other business related studies such as Marketing or Accounting, there are relatively few studies within Operations Management that take the human factor into account (Croson and Donohue, 2002; Bendoly et al., 2006). The field within Operations Management that explicitly considers the human factor is referred to as Behavioral Operations Management and it may be defined as follows (Loch and Wu, 2007): *"Behavioral Operations Management is a multi-disciplinary branch of Operations Management that explicitly considers the effects of human behavior in process performance, influenced by cognitive biases, social preferences and cultural norms."* Behavioral Operations Management is an area that has received increasing attention lately. This is for example witnessed by the establishment of a new college of the Production and Operations Management Society named "Human Behavior in Operations Management".

Studies in Operations Management can take the human factor into account by incorporating it into the model. This dissertation leaves the models as they are. Instead, we study the human factor in using those models. By taking the human factor and the use of planning software into account, we can contribute to explaining the reasons for low adoption rates of OR-based DSS, as well as to finding ways for increasing them. There are mainly three questions of interest for studying the human factor in transport planning:

- How do decision makers carry out logistics tasks if they do not make use of tools and techniques? Related questions are: what psychological mechanisms can explain systematic deviation from rational choice (Simon, 1955; Kahneman and Tversky, 1972; Tversky and Kahneman, 1973)? Can such general psychological mechanisms explain deviation from rational choice for logistics decisions (Schweitzer and Cachon, 2000; Corbett and Fransoo, 2007)? What is the role of organizational structure for increasing the capability of planners to deal with uncertainty (Galbraith, 1974; Tushman and Nadler, 1978)? What is the role of action variety and cognitive overload in planning (Fransoo and Wiers, 2006)?

- What is the current role of (OR-based) DSS in the planning process? Related questions are: does information technology impact performance directly or also indirectly, and which impact is stronger (Devaraj and Kohli, 2003; Devaraj et al., 2007)? What are specific system characteristics that can predict system adoption

(Venkatesh et al., 2003)? What is the role of organizational structure for increasing the impact of CAD technology on performance (Malhotra et al., 2001)? What benefits do practitioners see in specialized vehicle routing and scheduling systems (Golob and Regan, 2003)? Does the benefit of using marketing decision support systems differ depending on time pressure and cognitive style of decision makers (Van Bruggen et al., 1998)?

- What is the role of technological innovations in the logistics decision making process? Related questions are: how can variance in data presentation influence, support or hinder information processing and decision making (Larkin and Simon, 1987; Jarvenpaa, 1989; Vessey, 1991; Lurie and Mason, 2007)? Can a product centric approach solve coordination problems in logistics networks (Kärkkäinen et al., 2003a)? How can we support decision makers in taking advantage of information in a real-time monitoring environment (Lerch and Harter, 2001)?

1.5 Research objective and research questions

1.5.1 Concepts of fit from a theoretical perspective

Venkatraman (1989) distinguishes six different concepts of fit, which serve as blueprints for different interaction patterns of variables. Two of these concepts are used in this dissertation: moderating and mediating effects. Both concepts help to examine the links between task, technology, and performance more closely. Sometimes the impact of technology on performance depends on certain conditions. These conditions are then referred to as *moderaters* (Baron and Kenny, 1986). Moderating variables describe under which conditions effects are strong, weak, or non-existent. For instance, the use of DSS may be especially beneficial to decision makers with a low analytical cognitive style (Van Bruggen et al., 1998). By examining moderating effects, theory can be generated and tested about which uses of technology have comparatively stronger performance impacts (Carte and Russell, 2003). This will help managers to create conditions to exploit the benefits offered by technology.

Technology can influence performance in direct but also in indirect ways. For example, technology can facilitate the exchanges of orders and resources between planners (planner-interdependence), and planner-interdependence in turn may increase performance. The variable that explains how the independent variable (technology) affects the dependent variable (performance) is referred to as *mediator* (Baron and Kenny, 1986). Mediating variables explain how one variable is connected to another. The managerial implications are guidance for managers and software developers regarding which aspects to focus on to increase the performance impact of technology.

Ambiguity exists regarding the causal structure of technology and context (Markus and Robey, 1988). For example, some authors try to explain which organizational structure allows for technology innovation and adoption (Ettlie et al., 1984; Damenpour, 1991; Williams and Rao, 1997; Patternson et al., 2003; Wang and Tai, 2003), while others study the impact of technology on operations (Fulk and DeSanctis, 1995; Vickery et al., 2003). Organizational structure can act as a moderator for the performance impact of technology (Malhotra et al., 2001), but technology can also moderate the impact of organizational structure on performance (Andersen, 2005). Examining the mediator and moderator effects, we can draw conclusions when and how technology impacts decision making. This perspective also reflects the challenge of how to capitalize on the more timely and more accurate information provided by sophisticated monitoring technologies (Lerch and Harter, 2001; Lee and Özer, 2007).

1.5.2 Research questions

The research questions are roughly put in a sequence from traditional to modern planning support, and with an increasing focus on the role of the human factor.

Research question 1: What is the impact of OR-based and agent-based DSS presentation on perceived usefulness and what is the moderating impact of time pressure and cognitive style?

The first research question studies a rather traditional form of human-computer-interaction, in which users deliberatively initiate the algorithm provided by a DSS. Evidence from a wide of fields suggests that perceived usefulness, the extent to which users perceive a system to increase their performance in an organizational context, is an adoption antecedent for DSS (Davis, 1989; Chau and Hu, 2002; Amoako-Gyampah and Salam, 2004; Shih, 2004). However, theory provides little specific advice for designers on how to create perceived usefulness (Venkatesh et al., 2003). Literature regarding decision making under uncertainty studies psychological mechanisms that can create so-called ”illusory correlation” (Tversky and Kahneman, 1973, p. 207). Perhaps these insights can be exploited to create illusory correlation that may increase adoption rates of DSS? The first research question studies the impact of DSS presentation on perceived usefulness and to which extent this effect differs for decision makers with varying cognitive style and decision makers under varying time pressure conditions. We include the moderating variables cognitive style and time pressure, as they can explain difference in DSS usage (Van Bruggen et al., 1998; Banker and Kauffman, 2004). The argumentation is based on cognitive fit theory (Vessey, 1991; Vessey and Galletta, 1991) and a heuristic that can produce systematic bias for decision making under uncertainty (Kahneman and Tversky, 1972; Tversky and Kahneman, 1973).

Research question 2: What is the impact of order-oriented versus resource-oriented presentation structure on decision sequences and what is the moderating impact of time pressure and cognitive style

Humans tend to process information depending on the way it is presented on screen (Jarvenpaa, 1989). Therefore we may well influence the decisions users make by manipulating the presentation structure (Larkin and Simon, 1987). The second research question studies decision sequence, which we define as the order in which an individual selects a series of alternatives constituting a larger task. We examine two interfaces supporting the assignment of orders to resources: one with a structure dominated by orders, the other by resources. In the order-oriented presentation structure there is a vertical list of orders, and next to each order a list of resources for selection is provided. In the resource-oriented presentation structure, there is a vertical list of orders, and next to each resource a list of orders for selection is provided. Also in this research question, we study the moderating effect of cognitive style and time pressure.

Research question 3: What is the impact of the intensity of use of DSS on planning satisfaction and to what extent is this effect mediated by planner-interdependence

The first two research questions study the role of presentation of tools and data in the planning process. The third research question examines the role of the DSS as a whole and the way it is used in practice. An indirect effect of technology on performance might be stronger than a direct one (Devaraj and Kohli, 2003; Devaraj et al., 2007). The third research question aims to find out which of two uses of DSS has a greater impact on performance: (1) *use of isolated optimization*, modeled as the impact of intensity of DSS use on planning satisfaction, and (2) *use of collaborative optimization*, modeled as an indirect effect consisting of two parts: the impact of intensity of DSS use on planner-interdependence and the impact of planner-interdependence on planning satisfaction. The extent to which planner-interdependence mediates the direct effect of intensity of DSS use on planning satisfaction is the extent to which the use of collaborative optimization is more important for planning satisfaction than the use of isolated optimization.

Research question 4: What is the impact of planning effort on planning satisfaction and to what extent is this moderated by organizational structure

The fourth and last research question examines if the organizational structure hampers or enhances planners in realizing the benefits of monitoring technology. This is modeled as the effect of planning effort on planning satisfaction and the extent to which this is moderated by organizational structure. Our argumentation is based on Organizational information processing theory (Galbraith, 1973; Galbraith, 1974).

1.6 Research methodology

In order to answer these research questions we use two research methods: a lab experiment and a survey. Examining the impact of presentation requires data from several software packages that preferably only differ in their presentation. If software packages differ on a limited set of characteristics, conclusions will be more valid. The first research question examines how perceived usefulness varies for various DSS presentations. This aims at differences in perception and then it is preferable to compare two DSS that have the exact same functionality, and differ only in presentation to the user. Our first and second research questions further require a variance in time pressure. Such kind of specific data can be collected best in a lab experiment where the researcher can control the interfaces and the time pressure conditions. While generalizability of lab experiments tends to be low, internal validity is high (Galliers, 1991; Shadish et al., 2002).

The third research question compares a direct effect (use of isolated optimization) with an indirect effect (use of collaborative optimization). While internal validity is always a concern, generalizability of results is especially important for this research question and as a result, conducting a survey is preferable to a lab experiment (Field and Hole, 2004). Data regarding organizational structure, necessary for the fourth research question, can best be collected by a survey. We therefore choose the survey methodology for examining the third and fourth research question. The strong point of surveys are the high generalizability; the weaknesses are low internal validity and the possibility of systematic bias of the respondent and the researcher (Galliers, 1991).

The choice of research methods is somewhat atypical of Operations Management. The field of Operations Management has a strong focus on quantitative studies, often without empirical data. For example, Davidsson et al. (2005) examined 56 papers in the field of "agent-based approaches for transport logistics", and only found one deployed system. In a meta-study of 197 articles related to logistics service providing, 53% of the articles used empirical data (Krauth et al., 2007). However, within the subsample related to operations (75 articles), only 31% used empirical data. Especially lab experiments are hardly used in Operations Management. Bendoly et al. (2006) examine issues of six journals spanning the last 20 years and found only 51 studies based on lab experiments related to Operations Management, which indicates that only little research is done that studies behavioral aspects of decision making in a controlled setting. Conducting research with underrepresented methods, may advance the field to a greater extent than using overrepresented methods (Meredith, 1998). Hensher and Figliozzi (2007) underline the importance of examining behavioral aspects in transport and the value of empirical data.

1.7 Managerial contribution

As planning departments in transport companies are under pressure to ensure higher efficiency and service of transport orders at shorter notice, managers need to understand and manage the contribution of both the planner and the planning software to the planning process. This dissertation studies the role of the human factor in planning, focusing on planner-interdependence for increasing the performance impact of DSS and on the organizational structure for increasing the impact of planning effort on planning satisfaction. Further, managers need to get a better understanding of the benefits of technology, especially OR-based DSS, as these systems -imperfect as they may be in terms of their assumptions regarding problem formulations- clearly outperform human planners at delivering results with higher solution quality and at a higher speed (Blattberg and Hoch, 1990). This dissertation further focuses on how to give advice to planners, rather than on which advice to give. Given that planners make extensive use of technology for administrative purposes, communication with customers and increasingly with drivers as well, new ways of introducing the benefits of OR to the planning process may become possible. This dissertation studies how presentation of DSS and data as well as the role that planners assign to DSS as a whole may contribute to increase the adoption rates of OR-based DSS. The intended research is relevant not only to those responsible for the design of planning processes in transport companies, but also to developers of transport software.

1.8 Scientific contribution

The main academic contribution of this dissertation is to identify and empirically test the task-technology fit perspective for planning processes. This perspective allows to contribute to Behavioral Operations Management in two ways: (1) explain interaction of planners with planning technology, and (2) study the human factor in the planning process based on established theory.

Planning is often defined as *allocating order to resources over time* and as *re-planning* (Anthonisse et al., 1988; Hoogeveen et al., 1997). Based on the task-technology fit framework we can add another perspective: *planning is software use*. This allows to build on research from other fields such as Information Systems and Marketing on why and how users make use of information systems (Jarvenpaa, 1989; Vessey, 1991; Goodhue, 1995; Van Bruggen et al., 1998; Devaraj and Kohli, 2003; Devaraj et al., 2007). As a result, we can use established theory to explore reasons for low DSS adoption and ways of increasing them. Tasks such as choosing a restaurant (Jarvenpaa, 1989) or pricing (Van Bruggen et al., 1998) differ from typical logistics tasks such as finding the shortest route or the task of order-resource assignment. Also the technology constructs may need to be further specified for the purposes of Operations Management. Consider, for example, perceived usefulness which is a well-studied adoption antecedent (Chau and Hu, 2002; Amoako-Gyampah and Salam, 2004; Shih, 2004). Yet, summarizing the literature on technology acceptance, Venkatesh et al. (2003) come to the conclusion that there is still little specific advice regarding how to build systems that are perceived as useful. Likewise, we can build on established theory that perceived effort provides more leverage for increasing usage of a tool than perceived accuracy (Todd and Bensabat, 1999). While we can and should build on the argumentation, we do need to adapt it to logistics and test it in such a setting (Hopp, 2004).

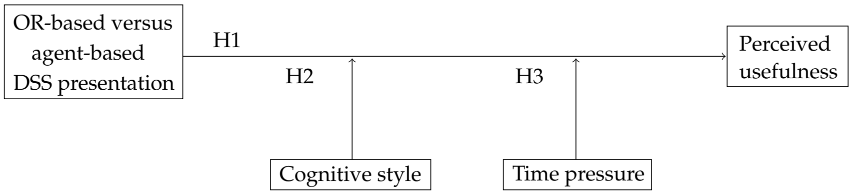
Chapter 2

Perceived usefulness of OR-based and agent-based decision support system presentations and the role of cognitive fit theory

2.1 Introduction

OR-based DSS have an image problem. Despite dramatic algorithmic advances, OR-based DSS are still used only to a limited extent (Bendoly et al., 2006; Loch and Wu, 2007; Dietrich, 2007). One reason for the low adoption rates of these systems may be that planners and their managers do not perceive these systems as useful.

Currently, DSS based on agent technology receive a lot of attention. Next to differences in the problem solving approach, OR-based and agent-based DSS differ in the way they communicate with users. OR-based DSS tend to use abstract and specific scientific terms such as column generation or traveling salesman (Desaulniers et al., 2005; Applegate et al., 2007). The terminology that agent-based systems use is highly similar to that of the real-world persons that these systems replace or support: business agents, procurement agents, production agents, distribution agents (Papazoglou, 2001), and advisory agents (Nissen and Sengupta, 2006). We argue that most people will find



The independent variable is categorical and we therefore cannot indicate the direction of the hypotheses

Figure 2.1: Perceived usefulness of OR-based and agent-based DSS presentations

that agent-based DSS are more closely related to the planning task, than the OR-based DSS - both in terms of terminology and mechanism of the problem solving approach.

In this chapter we examine the following research question: What is the impact of OR-based and agent-based DSS presentation on perceived usefulness and what is the moderating impact of time pressure and cognitive style? We include the moderating variables cognitive style and time pressure, as they lead to different usages of DSS in the decision making process (Van Bruggen et al., 1998; Banker and Kauffman, 2004). We hypothesize that agent-based DSS presentations are perceived as more useful than OR-based DSS presentations, and that the difference in preference is stronger for low-analytics rather than high-analytics, and decision makers under high time pressure rather than decision makers under low time pressure because we expect agent technology to be perceived as even more useful if the cognitive resources of decision makers decrease. Our argumentation is based on a heuristic that can explain systematic bias for decision makers assessing probability under uncertainty (Tversky and Kahneman, 1973) and on cognitive fit theory (Vessey, 1991; Vessey and Galletta, 1991; Shaft and Vessey, 2006). Cognitive fit theory builds on the work regarding biases in decision making and studies the match between data presentation and mental models in the head of the user.

2.2 Framework and hypotheses development

2.2.1 Main effect

From a software development perspective, the problem solving approach (algorithm) and the presentation of a DSS are clearly distinguishable. However, this distinction is

Table 2.1: Definition of constructs

Construct	Definition	References
DSS presentation	Terminology and mechanisms of the problem solving approach that a decision support system conveys to the user	Vessey, 1991; Vessey and Galletta, 1991
Cognitive style	The way in which subjects make decisions	Witkin et al., 1971; O'Keefe, 1989; Allinson and Hayes, 1996; Banker and Kauffman, 2004
Time pressure	The time allocated for conducting a task	Maule and Svenson, 1993; Hwang, 1994
Perceived usefulness	The extent to which users perceive a system to increase their performance in an organizational context.	Davis, 1989; Davis et al., 1989; Venkatesh et al., 2003

not always clear to the user. Users only see the user interface of the problem solving approach of the DSS communicated by graphics, progress indicators, and descriptions in a user manual. Users will often assume that the DSS (outside) presentation matches with the inside (algorithm). For users DSS and DSS presentation will, therefore, often be the same. We consider two aspects of the the DSS presentation: the terminology and the mechanism of the problem solving approach. The definition of DSS presentation and the other constructs used in this chapter are summarized in Table 2.1.

Our argumentation regarding how difference in terminology affects perceived usefulness builds on the availability heuristic which can introduce ”illusory correlation”, a term first used by Tversky and Kahneman (1973, p. 207). Decision makers which fall for the systematic bias of the availability heuristic do so by ”assessing availability, or associative distance” (Tversky and Kahneman, 1973, p. 208), which is illustrated in the following example. In an experiment, Tversky and Kahneman let two groups of subjects listen to sets of words. Some pairs had a smaller associative distance (e.g. fork-knife) than others (e.g. head-fork). The first group was asked to recall what they heard - this establishes a list of words pairs that are easy to remember. The second group was given some pairs and asked to remember how frequently they were mentioned. The pairs that the first group recalled often, were also the ones that the second group assessed as occurring more frequently. We argue that the same psychological mechanisms that produce systematic bias in decision making under uncertainty may also influence which perception of DSS. Consider for example, the approach of column generation (Desaulniers et al., 2005), which provides a technique for solving large linear problems typical for the OR domain. ”Columns” are no typical features of Operations Management environments in practice such as manufacturing firms or distribution centers, nor is there an obvious association between them. The benefit of using abstract terminology such as ”column generation” for describing problem solving approaches may be to facilitate focusing on the abstract problem. The large associative distance with a particular Operations Management problem, also reflects the wide applicability of these approaches. At the same time we contend that the terminology may create illusory distance with the task. In contrast, agent technology uses a terminology with a small associative distance: distribution agents suggest to solve distribution problems and scheduling agents suggest to solve scheduling problems. The terminology also often includes elements relevant to the Operations Management environment. Agent approaches for transport and logistics are typically modeled with truck agents and order agents, which ”communicate and make decisions" (Davidsson et al., 2005 p. 262; Mahr et al., 2008; Mes et al., 2007). The entities of trucks orders and the action of communicating or decision making belong to the natural environment of a transportation problem. The associative distance DSS description and real-world problem is higher for agent-based DSS than for OR-based DSS.

We base our discussion regarding the difference between agent-based and OR-based DSS presentations on cognitive fit theory, which examines the match between a task and the way data necessary for completing the task is presented (Vessey, 1991; Vessey and Galletta, 1991). Cognitive fit has been studied in different contexts such as learning effects for normative model based DSS (Ujwal et al., 2008), spreadsheet analysis (Chan et al., 2007), online shopping (Hong et al., 2005), software engineering (Shaft and Vessey, 2006) and geographic information systems (Smelcer and Carmel, 1997). Dunn and Grabski (2001) apply cognitive fit theory to explain differences in perception between traditional and modern accounting models.

Extending on the argumentation of cognitive fit theory we examine the match of problem solving approaches between human decision makers and DSS presentations. Humans tend to make use not only of cognition but also of perception and -in comparison to mathematical models- need less computations to reach good solutions (Applegate et al., 2007). Simon (1955) suggests that if users do not consider all the alternative solutions of a problem -and given the sheer size of typical OR problems that is unlikely and often impossible- they resort to some form of sequential information processing, which may be be informed by the way information is presented (Larkin and Simon, 1987).

OR-based DSS suggest to be based on heavy computation and mechanisms that require substantial education before they can be understood and applied. Planners are not always well acquainted with these problem solving approaches (Anthonisse et al., 1988). Like human planners, some OR algorithms -so-called approximation approaches- do not examine the complete solution space. However, human and OR algorithm differ in the choice of which parts of solution space they consider. For OR algorithms this choice is typically not guided by the structure in which data is presented. Agent-based systems on the other hand, suggest to make use of an mechanism that planners use themselves to solve real-life problems: negotiation. Admittedly, an in-depth understanding of an agent approach still depends on potentially complex coordination mechanisms, such as static or dynamic distribution of functionality among several agents, and the types of interdependence between them (Frayret et al., 2004; Davidsson et al., 2005). This list shows that an in-depth understanding of agent-based approaches can be just as challenging as OR-based DSS. But it is more likely that the user will find a mental model representing a problem solving approach for negotiation than for something as abstract and seemingly unrelated as column generation. As a result we formulate our first Hypothesis:

Hypothesis 1: Agent-based DSS presentations are perceived as more useful than OR-based DSS presentations.

2.2.2 DSS presentation and cognitive style

High-analytics are more likely to abstract and reach a solution based on the abstraction than low-analytics (O'Keefe, 1989; Van Bruggen et al., 1998). High-analytics can easily abstract a problem from the environment in which it is encountered (O'Keefe, 1989; Witkin et al., 1971). High-analytics are likely to apply a decision strategy that involves extracting the planning problem from its natural context and view pickup and delivery locations as a set of connected nodes. High-analytics and abstract DSS handle problems in a similar manner: first abstract a model, then solve it. Ability or predisposition to abstract can help high-analytics in two ways: they can form an abstract version of the task, thereby widening the set possible tools that can solve it. High-analytics can also form an abstract version of the DSS which makes the DSS more applicable to a wider set of problems. Low-analytics on the other hand, tend to be comfortable with a decision making process that involves replacing trucks for traveling salesmen and renaming orders to cities. An abstract DSS presentation conveys a complex problem solving approach, and while both high and low-analytics may experience difficulties with understanding complex models, high-analytics should find it comparatively easier to trust the model and accept its results. This leads us to the following Hypothesis:

Hypothesis 2: The dominance of agent-based over OR-based DSS presentations in terms of perceived usefulness is stronger for low than for high-analytics

2.2.3 DSS presentation and time pressure

Carrying out the same task becomes more difficult as time allocated for task completion decreases (Hwang, 1994). Under time pressure individuals are inclined to monitor available time which limits the cognitive resources available for conducting the task (Maule and Svenson, 1993). As a result of time pressure, cognitive resources available to establish cognitive fit might not suffice anymore to establish fit with problem solving approaches distant to the ones available in the head of the user. Next to limiting cognitive resources necessary for deliberative decision making, time pressure can also increase the influence of systematic biases in the decision making process (Maule and Svenson, 1993). Decision makers tend to use more heuristics and less deliberative forms of reasoning for decision making under time pressure (Hoghart and Makridakis, 1981; Van Bruggen et al., 1998). For example, subjects perceive higher risks and benefits for the same judgement task if it is carried out under time pressure (Finucane et al., 2000). Therefore, the illusory correlation created by an agent-based DSS can increase with time pressure. This leads us to the following Hypothesis:

Hypothesis 3: The dominance of agent-based over OR-based DSS presentations in terms of perceived usefulness increases with time pressure.

2.3 Method

2.3.1 Experimental design

The hypotheses are tested with data collected from a lab experiment (118 undergraduate and graduate students). We choose column generation (Desaulniers et al., 2005) as the OR-based DSS presentation for two reasons. First, the name per se is not complicated. Second, there is no straightforward interpretation how a set of generated columns can solve assignment problems. The experimental variables in the setup were DSS presentation (0 = agent negotiation, 1 = column generation) and time pressure (0 = high time pressure, 1 = low time pressure) resulting in a 2 * 2 factorial design. Cognitive style is a co-variate. We chose for a repeated measures design, collecting data on each of the four cells from each participant. Participants had a warm up phase and after that played four different planning phases. Each of these four planning phases related to a different cell of the 2*2 factorial design. There were two different sequences of these four planning phases. Participants were randomly designed to start with either agent-based DSS, or with the OR-based DSS. In the first two planning phases, participants experienced the low time pressure condition. The DSS of the third planning phases was the same as the

Table 2.2: Planning phases and DSS presentation

	low time pressure		high time pressure	
Warm up	agent negotiation	column generation	agent negotiation	column generation
Warm up	column generation	agent negotiation	column generation	agent negotiation

DSS of the first planning phases. Also on the second and fourth planning phases the same DSS was provided. However, in the third and fourth planning phase participants had the time pressure condition. The no time pressure condition allowed participants to get acquainted with the DSS. We controlled for the actual orders that were given to the participants. The sequence of planning phases for both randomly assigned groups is presented graphically in Table 2.2.

As all participants begin with two low time pressure planning days, we cannot draw conclusions regarding the effect of time pressure on perceived usefulness in general as it might be confounded with learning effects. However, this set up does allow examining the effect of time pressure on perceived usefulness of different DSS presentations.

Every participant was subject to four conditions resulting from the combination of time pressure and DSS. Such a set up is referred to as a within-subject design. Another possibility is between-subject design, where each participant is subject to only one condition, say column generation DSS under low time pressure. When choosing between within and between-subject design, a number of aspects can be considered (Maxwell and Delaney, 2004). Between-subject design is less economical in the sense that one would need four times the number of participants to collect as many observations as we did with within-subject design. In a within-subject study there is a problem related to personality traits such as cognitive style. Once all cognitive style tests are taken they need to be graded in order to know which cognitive style group the participant belongs to. And only then it is possible to assign the same number of low and high-analytics to each of the four cells. It is difficult to find such a large number of participants and rate their cognitive style quickly enough. For within-subject design, however, from all participants data on all conditions is collected and all cells are balanced. While these factors indicate that within-subject design is preferable, other factors indicate the opposite, mainly so-called learning effects (Maxwell and Delaney, 2004). For example, a participant might form an opinion about DSS in general during the first planning phase. The data collected from the second planning phase may be influenced by the first planning

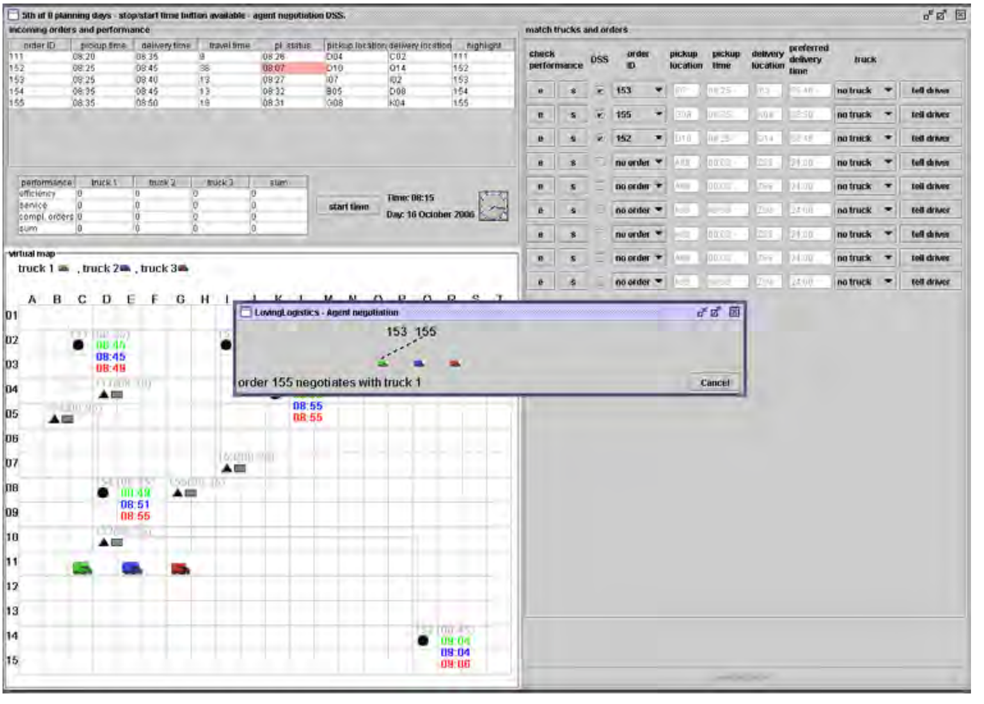


Figure 2.2: The lab experiment software with an agent-based DSS (presentation) in execution

phase, and there can be no clean comparison between the two observations anymore. By having some users begin with either one DSS the difference in learning effects can be examined (Maxwell and Delaney, 2004). Further, within-subject designs should only be considered if the effects do not persist between manipulations. We contend that most subjects will rate the system we ask them to rate, and that the effects do not persist. Furthermore, the sequence with which participants play the phases can be switched and the learning effects can be controlled for in statistical analyses.

2.3.2 Decision task

Participants assumed the role of a planner in a transportation company. On a given planning phase five orders arrive and three trucks are available for executing them. The participants had to make the following decision: which truck should execute which order? All five orders arrive within fifteen seconds real time. Planning performance was measured by two components: efficiency and service. Efficiency was measured by the distance that trucks drive empty and multiplying this with -1. Service was measured by multiplying the total number of late minutes of order deliveries with -30. The factor 30 was chosen after some experiencing with the software aiming at a balance between efficiency and service. As a result of this measurement, efficiency and service scores are always equal to or below zero. The software gives user the possibility to solicit information about performance consequence of order-truck combinations before making a decision. For each executed order, subjects received 3000 points which are added to efficiency and service score to give the total score.

2.3.3 The decision environment

The planning task basically consists of receiving orders, assigning orders to trucks and executing orders. The interface reflects these phases (a screen shot of the system used in the lab experiment is given in Figure 2.2). Arriving orders are indicated in the table on the top left of the interface and in the virtual map bottom left of the interface. The plan board ("match trucks to orders") on the right part of the interface allows users to choose orders and trucks by means of list boxes and communicate this decision with the "tell driver" button. On the bottom of the plan board (very bottom right corner of the interface) is the button "assign trucks" which initiates the decision support functionality. The virtual map on the bottom left gives a visual presentation of the geographic region that the participant is responsible for. It indicates pickup and delivery points (indicated by triangles and rectangles respectively), together with earliest pick-up time, preferred delivery time and for each truck the predicted delivery times if the participant would "tell the respective driver" this assignment at that moment. The virtual plan board simulates a real-time monitoring system including empty driving, animated pickup and delivery and transporting of goods. Once completely executed, an order is taken off the screen. The dashboard in the middle of the left part of the interface indicates efficiency, service and total scores. These are updated as soon as the "tell driver" button is clicked. Further there is a digital and analog representation of simulated time. Under low time pressure participants, could stop time. During stopped time, trucks were standing still but participants could still use the functionality for inquiring about efficiency and service impact of order-truck combinations. Under high time pressure functionality to stop time was disabled.

Both DSS presentations make use of the same algorithm which works as follows: First the DSS calculated efficiency and service scores for each order-truck combination and then choose the combination with the highest profit. Then order and truck of the selected combination are removed from consideration set and the next order-truck combination with the highest profit is selected. At the most it was possible to select 3 orders. In order to leave a strong impression on the user, we artificially prolonged execution of the DSS. It took 15 simulated minutes for the DSS to calculate 3 orders, and less if only one or two orders were inquired. When executing a DSS under time pressure, the execution often takes so long that services scores are affected negatively. Say if all orders are late when initiating the DSS, the execution time will result in additional -180 points when the DSS only included one order, -300 for two orders, and -450 for three orders.

2.3.4 The process of a single planning day and using the DSS

Subjects interact with the interface typically as follows. The planning phase begins with orders that arrive in the incoming orders table; their delivery and pickup locations then pop up on the virtual map. Participants can select order-truck assignments themselves or ask the DSS for a suggestion. A description of how the specific DSS worked was given in the handbook (Table 2.3).

In order to initiate the DSS functionality the participant needs to select at most three orders, by checking ″DSS″ check boxes and press the ″assign trucks″ button, respectively. Depending on the amount of orders that are included subjects have to wait for between six and fifteen minutes simulated time, which are six and fifteen seconds real time, respectively). The DSS process gives the solution by selecting respective entries in the truck list. Participants can leave the order-truck assignment unchanged and immediately communicate them to the driver. By selecting different orders or trucks from the respective lists subjects can ″overwrite″ the solution suggested by the DSS.

2.3.5 Setup of the participant session

The complete session of the lab experiment took about 1.5 hours. The participants received a monetary reward, and the best three participants were given an extra payment.

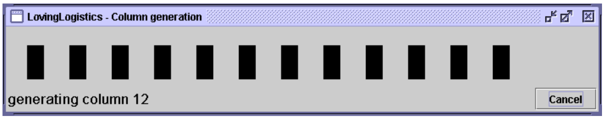


Figure 2.3: Progress bar for column generation DSS during execution

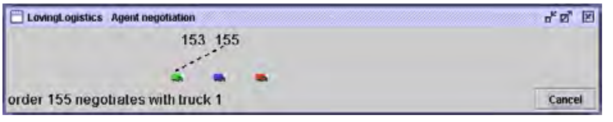


Figure 2.4: Progress bar for agent negotiation DSS during execution

The session started with an introduction to the system. During this introduction special attention was paid to the DSS presentations and participants were asked to read through the description of both DSS presentations. Then the participants started using the system. Participants played a total of nine planning phases. The first phase was a warm up session, and students were encouraged to ask questions about the system. The planning phases one through five relate to another interface effect that is not reported on here. In these four planning phases, the participants had to assign orders to trucks by themselves without being able to use decision support. These four phases allowed the participants to get well acquainted with planning and develop a mental model of the task.

2.3.6 Experimental conditions

We have developed a description of both DSS presentations and also included them in the manual for the lab experiment. Both by text and visual presentation users were reminded of the different problem solving approaches. For the text in the manual refer to Table 2.3. The progress bars presented during execution of the DSS functionality are presented in Figures 2.3 and 2.4. During execution of a DSS, visual representation and text message were updated every second.

Table 2.3: Description of decision support systems in the participant manual

Decision support system (DSS): column generation When the ”assign trucks” button is pressed the following happens: The system calculates the solution with an algorithm based on column generation. This is a mathematical procedure which uses the method of column generation and linear programming. It works like this: If you want to have the best solution you have to generate all possible solutions, calculate how good they are and then select the best. Since there are so many possible solutions, it is not possible to evaluate all. Column generation generates a set of solutions and evaluates them by looking at only a specific aspect (=columns), and then selects the best. The trick is to choose a ”good” set of columns for evaluation. The algorithm selected for LovingLogistics evaluates only those subsets that contain the order-truck combination with the highest total scores. This algorithm will find a good solution in most situations but not always the best.
Decision support system (DSS): agent negotiation When the ”assign trucks” button is pressed the following happens: for every order and truck there is a software module (agent) taking care of it. These agents do what clients and truck drivers would do if they were to decide which truck driver should do which order: they negotiate. In addition, there is a managing agent, which is coordinating the negotiation. First, every order agent negotiates with each truck agent to determine the performance. As a result every order agent has a ranking of which truck it would prefer. Then the managing agent asks each order about its best order-truck combination. The managing agent selects the best order-truck combination of all orders. The managing agent will repeat the process of selecting the best order-truck combinations until all orders have been assigned a truck. This algorithm will find a good solution in most situations but not always the best.

LovingLogistics is the name of the software used for the experiment

Table 2.4: Measurement of perceived usefulness and self-reported cognitive fit

Perceived usefulness, Cronbach α = 0.90 (based on Davis, 1989):	
Compared to the warmup interface, this interface (including the DSS) ...	
PUF1	... enabled me to make decisions more quickly
PUF2	... enabled me to increase my productivity
PUF3	... enabled me to increase my performance
Self-reported cognitive fit (developed by us):	
The decision support system that I just used ...:	
SRCF	... had a decision making process similar to my decision making process

all items measured on a 5 point Likert scale

Table 2.5: Measurement of perceived ease of use and rival explanations

Perceived ease of use, Cronbach α = 0.86 (based on Davis, 1989):	
Compared to the warmup interface, this interface (including the DSS) ...	
PEU1	... was easier to use
PEU2	... was easier to understand
PEU3	... was clearer
PEU4	... was more flexible
Rival explanations (developed by us):	
The decision support system that I just used ...:	
RIVAL1	... provided results that I can trust
RIVAL2	... gave me reliable results
RIVAL3	... made me hesitate using it
RIVAL4	... made me confident using it
RIVAL5	... could deal well with lots of data*
RIVAL6	... has an algorithm that is easy to understand
RIVAL7	... has an adequate algorithm for the problem

The self-reported cognitive fit (SRCF) item was put in one questionnaire together with the 7 Rival Explanation items. The self-reported cognitive fit measure was the 6th in the list of the 8 items.

* RIVAL5 is also referred to as perceived computation capacity

all items measured on a 5 point Likert scale

Table 2.6: Objective measurements

Variable	Measurement
Efficiency	- Distance traveled empty
Service	- Number of late minutes
Total score	(3000 * Number of completed orders) + Efficiency + 50 * Service
DSS usage	Amount of times a DSS was initiated
Amount adopted suggestions	Number of times that a participant executed an order with the truck that was suggested by the DSS
Duration real time	Number of minutes that the whole planning phase took in terms of real time
Simulation time	Game time which was 60 times faster than real time. Under low time pressure participants could pause the game with a button.
Cognitive Style	Score from the Hidden Figures Test, a Gottschaldt-Thurstone adoption of the Embedded Figures Test (French et al., 1963; Feldberg, 2006)

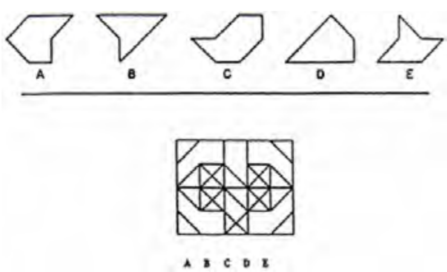


Figure 2.5: Example of the Hidden Figures Test

2.3.7 Measurement

In a specific planning phase participants have a DSS available that either has a column generation or agent negotiation presentation. The time pressure variable can have the values low or high. Cognitive style was measured as a co-variate by means of the Hidden Figures Test (French et al., 1963), a modified version of the Embedded Figures Test (Witkin et al., 1971). An example is presented in Figure 2.5. Both the Hidden Figures and the Embedded Figures Test measure the extent to which subjects can identify figures in complex patterns. The Embedded Figures Test gives a set of problems to the subject and measures how long it takes to find solutions. The Hidden Figures Test gives a set of problems and measures how many are solved within a given time frame (2 * 10 minutes). If a subject abstracts these patterns well from their context, she is a high-analytic; otherwise a low-analytic. The management literature tends to distinguish between low and high-analytics, while psychological literature tends to name the same categories field-dependent and field-independent (Bensabat and Dexter, 1982). The minimum score was -3.25, the highest 29.75 (the maximum would have been 32, each correct answer gave a point, each incorrect answer incurring a deduction of .25). We use median split to distinguish between low and high analytics; the median was 11.88 (mean=12.16, standard deviation=7.6).

The measurements for perceived usefulness and perceived ease of use were taken from Davis (1989) and van Bruggen et al. (1998). The set of rival explanations is developed based on the DSS usage literature, addressing aspects such as trustworthiness, perceived reliability, confidence in results, adequacy and ease of understanding the algorithm (Payne, 1982; Anthonisse et al., 1988; Singh and Singh, 1997; Golob and Regan, 2003). The perceptive measures are presented in Table 2.4 and Table 2.5.

Table 2.6 gives an overview of the objective measurements. Table 2.7 presents statistics describing the lab experiment. Both low and high-analytics have a higher total score during low time pressure. Under each time pressure condition, high-analytics were getting higher total scores than low-analytics. Under low time pressure a planning phase took more than four real minutes for both groups. High time pressure planning phases took about two real minutes. We also measured how long planning took in terms of simulated time. Under low time pressure, when subjects could pause time, planning phases of both groups took about 28 simulated minutes, under high time pressure duration about doubled. This indicates that participants made good use of the possibility to start and stop time under the low time pressure condition. *DSS usage* describes how

Table 2.7: Descriptive statistics

	Mean			
	low-analytics		high-analytics	
Time pressure	low	high	low	high
Score	8936.83	4555.61	9413.47	4736.71
Duration real time (min.)	4.59	2.00	4.26	2.00
Duration simulated time (min.)	28.64	57.72	28.65	55.98
DSS usage	2.39	1.44	2.22	1.20
Amount adopted suggestions	3.15	2.64	2.92	2.59

often participants initiated the DSS. Low analytics asked on average 2.39 time during a low time pressure planning phase, high analytics somewhat less often (2.22 times). Under high time pressure both groups used the DSS less (1.44 times for low analytics and 1.20 times for high analytics). The pattern regarding amount of adopted suggestions is similar. Suggestions were adopted more often by low-analytics than high-analytics, and more often under low time pressure than under high time pressure.

We test our hypotheses following the approach of van Bruggen et al. (1998) which examine the performance impact of Marketing DSS including the moderating effects of cognitive style and time pressure. The following Equation is used to test the effects of DSS presentation, cognitive style and time pressure and their interactions:

$$\begin{aligned} \textit{Dependent variable}_{it} = \; & \alpha_0 + \alpha_1 DSS_t + \alpha_2 COGN_i + \alpha_3 TIPR_t + \alpha_4 DSS_t * COGN_i \\ & + \alpha_5 DSS_t * TIPR_t + e_{it} \end{aligned} \tag{2.1}$$

whereas *DSS* refers to the dummy variable *DSS* (either column generation or agent negotiation), *TIPR* is a dummy variable referring to time pressure (either low or high) and *COGN* refers to Cognitive Style measured by the score of the Hidden Figures Test. Individual variables are referred to with index i, manipulated variables carry index t. As perceived usefulness is influenced to some extent by perceived ease of use (Davis et al., 1989; Amoako-Gyampah and Salam, 2004; Shih, 2004), we control for perceived ease of use. We also control for *sequence* and actual problem instance (*problem instance set*) that the subject was working with. The dependent variable of our conceptual model is perceived usefulness; however we also test Equation 2.1 with *self-reported cognitive fit (SRCF)* and rival explanations *(RIVAL1-7)* in order to examine which best explains perceived usefulness.

In order to analyze the data we need an approach that can model covariances between the observations and means of the data separately. This can be done with SAS Proc Mixed (SAS Institute, 2004), which can test general versions of General Linear Models (a general version of, for example, ANOVA). The covariance between the four observation of each individual are modeled as what the SAS Guide refers to as covariance parameters, the effects of the known explanatory variables (DSS, cognitive style, time pressure and control variables) are modeled as what the SAS Guide refers to as fixed effects.

2.4 Discussion of results

Hilbe (2007) suggests finding the best fitting model in a sequential approach: start with a model, observe which factors are not significant, then run a second model leaving out the factors which are not significant in the first one. If the second model has the same significant factors one should take the one with the better goodness of fit factors. Based on literature we formulate a restricted model, which we compare to the full model. We choose to use the results from the full model only if the interaction term is significant, and if the goodness of fit indicators are more preferable. As we do not have hypotheses formulated for the term COGN*TIPR we do not take this term into consideration when deciding on the model.

The fit statistics of the reduced and the full model with perceived usefulness as dependent variable are given in Table 2.8. First it should be noted that the difference between both models in negative binominal log likelihood (-2 log likelihood) is only small (less than 1%). However, AIC and BIC are smaller for the reduced model which is preferable in case significance values are the same (Hilbe, 2007). In the full model the three way interaction (*COGN*x*TIPR*x*DSS*) is not significant. The negative binominal log likelihood index is higher for the full model which is preferable. To summarize, the model statistics do not give a clear indication which model is better. However, the reduced model has been applied in earlier research (Van Bruggen et al., 1998) and, therefore, is the one that we will use here as well.

Table 2.8: Results for perceived usefulness, perceived computation capacity and self-reported cognitive fit

		perceived usefulness		perceived computation capacity		self-reported cognitive fit	
Source of Variation	DF	F	Sig.	F	Sig.	F	Sig.
DSS	1	3.62	0.0897	5.1	0.0556	7.92	0.0236
cognitive style	1	0.00	0.4875	2.78	0.1196	2.7	0.1228
time pressure	1	4.16	0.0751	9.02	0.0172	7.92	0.0238
DSS * cognitive style	1	6.10	0.0408	6.62	0.0348	1.48	0.1952
DSS * time pressure	1	7.12	0.0301	6.16	0.0401	3.04	0.1092
problem instance set	1	0.08	0.4238	11.68	0.0081	0.04	0.4469
sequence	1	0.02	0.4642	0.02	0.4579	2.14	0.1505
perceived ease of use	1	463	< 0.0001	140.02	< 0.0001	92.26	< 0.0001

one-tailed significances, standardized coefficients

assessment of model based on fit statistics (Hilbe, 2007):

Measure	rest. model	full model	rest. model	full model	rest. model	full model
-2 Res Log Likelihood	1125.2	1125.8	1225.3	1228.9	1272.0	1275.6
AIC (smaller is better)	1129.2	1129.8	1229.3	1232.9	1276.0	1279.6
BIC (smaller is better)	1134.8	1135.4	1234.9	1238.4	1281.6	1285.1

2.4.1 Main effect

Hypothesis 1 states that agent-based DSS presentations are perceived as more useful than OR-based ones. The results for Equation 2.1 with the dependent variable *perceived usefulness* are shown in Table 2.8. There is a significant interaction effect of DSS and cognitive style as well as DSS and time pressure. As a result of these interaction effects, we need to examine the interaction effects before we can make a statement whether agent-based DSS are perceived as more useful than OR-based in general.

We argue that agent-based DSS presentations are as perceived more useful because of the better match between DSS presentation and mental problem solving model of the user (Vessey, 1991). We tested this argument by running Equation 2.1 with *self-reported cognitive fit (SRCF)* as dependent variable. The result are shown in Table 2.8. Unlike perceived usefulness, there are no significant interaction effects. Self-reported cognitive fit does not vary as a result of time pressure or cognitive style. Examining the means reveals that *self-reported cognitive fit* is higher for agent negotiation DSS presentation (mean = 2.3414) than for column generation DSS presentation (mean = 2.1877).

We also run the Equation 2.1 with the seven rival explanations *(RIVAL1-7)* as defined in Table 2.4. Of these seven rival explanations only one, RIVAL5, resulted in significant findings of DSS or one of its interaction terms. The wording of the RIVAL5 item is "The DSS that I just used ... could deal well with lots of data" and we refer to RIVAL5 as *perceived computation capacity*. For perceived computation capacity there are significant interaction effects between DSS presentation and cognitive style (F=6.62; p=0.0348) as well as DSS presentation and time pressure (F=16; p=0.0401). As a result, the effect of DSS presentation on perceived computation capacity depends on cognitive style and on time pressure.

The other six RIVAL explanations noted in Table 2.4 did not result in significant results that involve DSS presentation. Apparently, subjects did not think that either DSS was giving results that are more reliable (RIVAL2), or that either DSS made them hesitate or confident using the DSS (RIVAL3 and RIVAL4). Further subjects did not find that either DSS was more trustworthy (RIVAL1), easier to understand (RIVAL5), or more adequate (RIVAL7) than the other. Further we tested Equation 2.1 with perceived ease of use as a dependent variable and found no significant effect regarding DSS presentation. Also there is no significant direct or interaction effect of DSS presentation on frequency of using DSS (DSS usage).

2.4.2 Interaction of DSS presentation and cognitive style

Hypothesis 2 states that the dominance of agent-based over OR-based DSS presentations in terms of perceived usefulness is stronger for low than for high-analytics. The results presented in Table 2.8 show that the interaction effect between DSS and cognitive style is significant at the 5% level (F=6.10, p=0.0408). We identify the interaction by examining the means presented in Figure 2.6 and Table 2.9. The perceived usefulness ratings of agent negotiation DSS presentation is the same for both groups, however, the perception regarding column generation differs. High-analytics perceive the column generation DSS presentation equally useful to the agent negotiation DSS presentation. In contrast, low-analytics perceive the column generation DSS presentation as less use-

Table 2.9: Means for identifying interaction effects

	cognitive style			
	column generation		agent negotiation	
	low-analytics	high-analytics	low-analytics	high-analytics
perceived usefulness	2.29	2.44	2.48	2.44
perceived computation capacity	2.35	2.30	2.30	2.11
	time pressure			
	column generation		agent negotiation	
	low time pressure	high time pressure	low time pressure	high time pressure
perceived usefulness	2.49	2.25	2.45	2.48
perceived computation capacity	2.36	2.33	2.38	2.06

ful (mean = 2.29) than the agent negotiation DSS presentation (mean=2.48). The results partially support Hypotheses 1 and 2. Agent-based DSS presentations are perceived as more useful than OR-based DSS presentations (Hypothesis 1), however only for low-analytics. The dominance of agent-based over OR-based DSS presentations in terms of perceived usefulness is stronger for low than for high-analytics (Hypothesis 2), however for high-analytics this dominance seems to not exist.

Perceived computation capacity also has a significant interaction effect between DSS and cognitive style ($F=2.62$; $p = 0.0348$), and we identify it based on the means presented in Figure 2.6 and Table 2.9. High-analytics do perceive a difference, and they find the column generation DSS presentation to have higher computation capacity than the agent negotation DSS presentation.

The results suggests that high-analytics find both DSS presentations equally useful. However, they do perceive a difference in computation capacity. For low analytics it is the other way around. They find the agent negotiation DSS presentation more useful, but perceive no difference regarding perceived computation capacity. At first, this is a paradox. One group perceives a difference in computation capacity and the other in perceived usefulness. The DSS that is perceived to have higher computation capacity by one group, is perceived less useful by the other group. Refining cognitive fit theory in a fashion similar to Shaft and Vessey (2006) can explain this paradox.

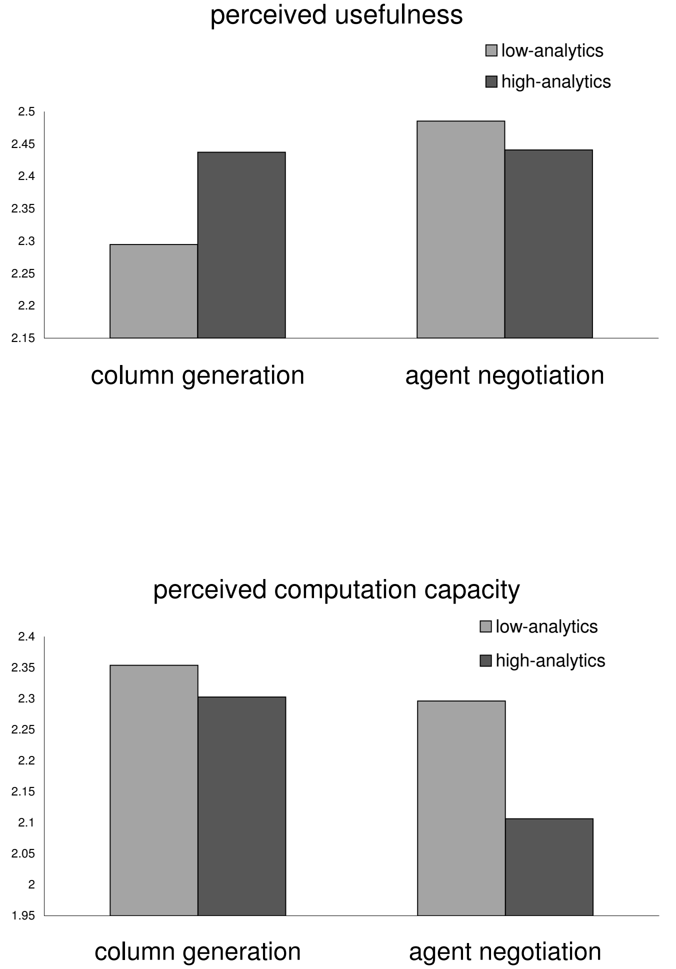


Figure 2.6: Interaction pattern of DSS presentation and cognitive style

Our refinement of cognitive fit theory basically suggests that users differ in their mental models. We argue that all users find the agent-based DSS closer to their own way of decision making (mental model representing the task), than the OR-based DSS. This is reflected in the finding that all users rate self-reported cognitive fit higher for the agent negotiation DSS presentation than for the column generation DSS presentation. In addition to a mental model representing the task, high-analytics seem to have a mental model for abstract problem solving approaches, which informs them that abstract problem solving approaches have higher computation capacity. This is reflected in the higher perceived computation capacity scores given to OR-based DSS presentations only by high-analytics. Low-analytics perceive no difference in computation capacity between the two DSS presentations. The differences in mental models may lead to differences in perception of DSS characteristics and perceived usefulness in the following way. For low-analytics, self-reported cognitive fit has a positive impact on perceived usefulness. For high-analytics, the benefit of cognitive fit of the agent negotiation DSS presentation is outbalanced by a seeming lack in computation capacity, resulting in no clear preference for either agent negotiation or column generation DSS presentation.

2.4.3 Interaction of DSS presentation and time pressure

Hypothesis 3 states that time pressure strengthens the dominance of agent-based DSS presentations over OR-based DSS presentations in terms of perceived usefulness. The results presented in Table 2.8 show that the interaction effect between DSS and time pressure is significant at the 5% level (F=7.12; p=0.0301).

We identify the interaction by examining the means presented in Figure 2.7 and Table 2.9. Under low time pressure, both DSS presentations are perceived as equally useful. Under high time pressure, the agent negotiation DSS presentation remains equally useful, while the column generation DSS presentation is perceived as less useful. As time pressure increases, perceived usefulness of column generation DSS presentation decreases, while it stays the same for agent negotiation DSS presentation. The results partially support Hypotheses 1 and 3. Agent-based DSS presentations are perceived as more useful than OR-based DSS presentations (Hypothesis 1), however only under high time pressure. The dominance of agent-based over OR-based DSS presentations in terms of perceived usefulness is stronger as time pressure increases (Hypothesis 3),

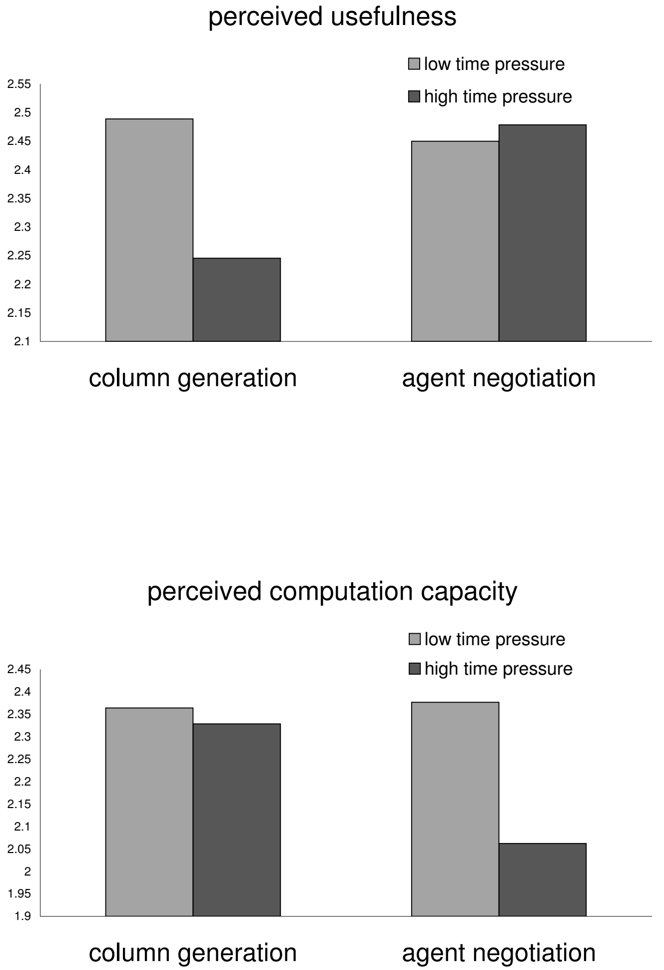


Figure 2.7: Interaction pattern of DSS presentation and time pressure

however for low time pressure this dominance seems to not exist.

Based on the means presented in Figure 2.7 and Table 2.9 we identify the interaction effect of DSS presentation and time pressure for perceived computation capacity. Like for perceived usefulness, there is no difference between both DSS presentation under low time pressure. Unlike for perceived usefulness, the rating of the agent negotiation DSS presentation decreases under time pressure. Again the data suggests a contradiction. One DSS decreases in perceived computation capacity, but it is the other DSS that decreases in perceived usefulness. At first the statistics suggest that under time pressure the increase in perceived computation capacity of column generation DSS presentations can explain the increase of perceived usefulness of agent negotiation DSS presentation. But that seems unlikely. We contend that under high time pressure the effect of cognitive fit is stronger than the effect of perceived computation capacity. Apparently, the cognitive fit relates to perceived effort of using a DSS which can better predict adoption than perceived accuracy, closely linked to perceived computation capacity (Todd and Bensabat, 1999). Our data suggests, that the dominance of perceived effort over perceived accuracy for predicting DSS adoption might even increase with time pressure.

To summarize, we cannot draw a clear conclusion regarding Hypotheses 1, that agent-based DSS presentations are always perceived as more useful than OR-based DSS presentations. Sometimes they are perceived as equally useful. However, all subjects report that agent-based DSS presentations have higher level of cognitive fit than OR-based DSS presentations. The self-reported cognitive fit leads low-analytics to perceive agent-based DSS presentations as more useful. Averaged over both time pressure conditions, high analytics do not find agent-based DSS presentations more useful than OR-based DSS presentations. We argue that is because of a seeming lack of agent-based DSS presentations in comparison to OR-based DSS presentations in terms of computation capacity. However, as time pressure increases, all users perceive OR-based DSS presentations as less useful. This is the case even though subjects find that under high time pressure OR-based DSS presentations have higher computation capacity than agent-based DSS presentations.

2.5 Conclusions

We have examined the effect of two DSS presentations on perceived usefulness and how this effect is moderated by cognitive style and time pressure. Low-analytical decision makers and decision makers under time pressure perceive agent-based DSS presentations as more useful. The hypothesized underlying mechanism is cognitive fit, a theory that was first used to explain why sometimes tables give better decision support and sometimes figures (Vessey, 1991). This theory has since been applied to a variety of contexts. However, since two major buildings blocks -mental model of the task and cognitive fit- occur in the head of the user, problems related to measurement remain. Aspects related to measurement of mental models and cognitive fit theory have recently found renewed interest (Chan et al., 2007; Ujwal et al., 2008). We have addressed this problem by testing whether other explanatory factors can be excluded.

We use data collected from students to test theory aimed at experts in decision making: planners. The question is whether making such a generalization is valid. Obviously, students are not expert planners which poses a threat to external validity. On the other hand, research has shown that students can serve as "surrogates for managers" (Remus, 1986). While caution should be taken when applying the results to practice, we contend that this study does provide valuable insights for developers and buyers of OR-based DSS, especially in the light of the suboptimal adoption rates of these systems.

To examine the extent to which DSS create illusory correlation, developers and buyers of software can ask questions like: Are the entities and computation processes presented in a manner directly and clearly related to the business problem? Is the information and data processing approach presented in a manner that is immediately intuitive? If not, can it be changed to more closely reflect the mind set of planners that will use the software? For example, the system should give pictures of trucks for trucking companies and pictures of cars for transport companies operating with cars, e.g. express transport services within cities. Showing pictures of vehicles that do not correspond to the context or possibly even worse, a traveling salesman, or columns being generated might only provide unnecessary distraction. Using symbols and terminology distant to the task may cause the user to question the appropriateness of the tool.

Our data suggests that creating cognitive fit may suffice to convince low-analytics about the usefulness of a DSS, however high-analytics also consider perceived computation capacity. We suggest a sequential approach: first establish cognitive fit, and then establish perceived computation capacity. For example, explain the algorithm in a manner that is short and appealing to create the perception of cognitive fit, and then allow users to learn more details about the approach which may reassure high-analytics that a sophisticated algorithm was used. In order to provide high-analytics with background information on the algorithm, we suggest a link " if you are interested in the mathematics we use, click here". However, this link should not be very prominent in order not to disturb low-analytics.

The problem solving approach that is used by the agent-based DSS presentation in our experiment is negotiation. We argue this leads to higher ratings of perceived usefulness than approaches as abstract and seemingly distant to the task as, for example, column generation. Next to negotiation there are other generic problem solving approaches that planners may be acquainted with. For example, humans sometimes solve problems by sequential processing based on presentation structure (Simon, 1955; Larkin and Simon, 1987), or by assessing spatial characteristics (Applegate et al., 2007). Further research may examine under which conditions DSS presentations with such more human like problem solving approaches can create cognitive fit and contribute to increasing adoption rates. Further research may also take the OR approaches as a starting point and search for ways to convey the underlying mechanism in a way that users can easily relate to. For example, column generation may be described as an approach which first divides a large problem into small ones and then calculates various versions which differ only slightly from each other to find a the best solution.

This study contributes to the largely uncharted territory of Behavioral Operations Management by giving a possible explanation for low adoption rates of OR-based DSS as well as a handle to increase them. In addition, Behavioral Operations Management may benefit from the notion of mental models as a framework to study the cognitive process of decision makers.

This research points to a possibly invalid assumption that can be further examined by studies aiming to contribute to Behavioral Operations Management. Self-reported cognitive fit varies for both DSS presentations, but ease of understanding does not. At first it is surprising that self-reported cognitive fit and items addressing ease of understanding have different results. After all, if decision makers state that the DSS "has a decision making process similar to their own" this DSS should also be easy to understand. Alternatively, this result might point to a basic assumption that needs to be dropped: decision makers might not always find their own decision making process easy to understand. Further research could interview decision makers in a field study to explore how planners describe their own decision making process and which characteristics are reflected by DSS and which are not.

Chapter 3

Order-resource assignment and the role of presentation structure: experimental evidence

3.1 Introduction

Deciding which resource should execute which order can be a simple task. For example, you simply match the first order in the order list with the first resource in the resource list. Then you can proceed to match the second order in the order list with the second resource in the resource list and so forth. Alternatively, you can also use an OR-based DSS to explore solution space and decide which overall assignment of all orders and resources under your responsibility is the best. In general, the solution quality is higher when using an OR-based DSS than when using manual approaches as the one described above. However, often the perceived effort is a stronger argument against using an OR-based DSS than the perceived increase in solution quality is an argument in favor (Todd and Bensabat, 1999). The effort related to using OR-based DSS may be a reason why practitioners use them to such a low extent (Bendoly et al., 2006; Dietrich, 2007; Loch and Wu, 2007).

How do planners make decisions if they do not use models? In principle a decision maker may choose a rational problem solving approach, which typically implies evaluating all possibilities and then selecting the best (Simon, 1955). However, the size of typical problem instances in Operations Management, time pressure and the distractions from frequent client interactions may force planners to resort to bounded rationality (Simon, 1955). Then decision makers may follow some form of efficient information processing heuristic, such as sequential processing based on the presentation structure (Larkin and Simon, 1987). The processing order of decisions, referred to as *decision sequence*, that planners make will then reflect the presentation structure of the data the decision is based on. Decisions in Operations Management are often based on data received or stored electronically, and this will even increase with adoption of sophisticated monitoring technology (Lerch and Harter, 2001; McFarlane and Sheffi, 2003; Lee and Özer, 2007). If presentation structure can predict decision making we may sort data such that planners are more likely to choose solutions advised by OR algorithms.

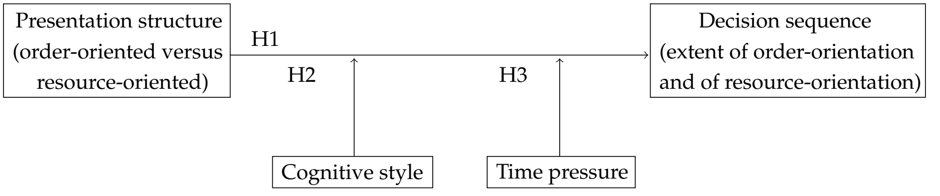
We study if presentation structure can predict decision sequence for a typical Operations Management task: assigning orders to resources. Reflecting the main elements of the order-resource assignment decision, and also inspired by the item-centric approach (Kärkkäinen and Holmström, 2002; Kärkkäinen et al., 2004; Holmström et al., 2006), we distinguish between *order-oriented and resource-oriented presentation structures*, labeled after the dominant factor in the presentation structure. The order-oriented presentation structure contains a vertical list of orders, and next to each order a list of resources can be chosen from. The resource-oriented presentation structure contains vertical list of orders, and next to each resource a list of orders can be chosen from.

We examine the following research question: what is the impact of order-oriented versus resource-oriented presentation structure on decision sequences and what is the moderating impact of time pressure and cognitive style? We expect that the effect of presentation structure on decision sequence will be stronger for decision makers with a low-analytical rather than a high-analytical cognitive style, and decision makers under high rather than low time pressure, because we expect subjects to more closely follow "efficient information processing heuristics" as their cognitive resources decrease.

3.2 Framework and hypotheses development

3.2.1 Conceptual model

Figure 3.1 shows our conceptual model. The basic effect is the impact of the presentation structure on decision sequences. Not only presentation structure, but also tasks



The independent variable is categorical and we therefore cannot indicate the direction of the hypotheses

Figure 3.1: Presentation structure and decision sequences

may influence the way people gather information and make decisions (Jarvenpaa, 1989). However, in this study we hold the task constant by only considering order-resource assignment. In addition, we model the moderating effect of cognitive style and time pressure.

3.2.2 Decision sequence

Assigning orders to resources in a sequential manner consists of a series of choices in which the decision maker selects a resource for executing a certain order. Here we only consider the simple case in which one resource suffices to execute an order, and all resources can in principle execute all orders. The amount of resources may be larger or smaller than the amount of orders and subjects may assign more than one order to a resource. We illustrate the concept of decision sequence for an order-resource assignment task with the following example: Consider the problem of assigning two orders (order A and order B) to two resources (resource X and resource Y). The first planner assigns order A to resource X and then, order B to resource Y. The second planner assigns order B to resource Y, and then order A to resource X. Both planners have the same decision outcome, but different decision sequences (AX-BY or BY-AX). We further distinguish order-orientation and resource-orientation as characteristics of decision sequences for order-resource assignment tasks. Consider for example only the orders in the decision sequence of the first planner. The first order is order A, the second is order B. The sequence of orders (first A, then B) is the same as the sequence of the orders in the task list. However, for the second planner, the sequence of orders in the decision sequence (first B, then A) is not the same as the sequence of orders in the task list. The order-orientation of the decision sequence of the first planner is higher than the one from the second planner. We define order-orientation of a decision sequence as the extent to which the orders reflect the sequence of orders in the task list. Note that the order-orientation and resource-orientation do not need to coincide. Our dependent variable is a more granular version of decision strategies which are defined as ”the method by which people acquire and combine information to make decisions” (Jarvenpaa, 1989, p. 286).

Decision sequence and the actual outcome of an order-resource assignment task are related only in an indirect manner. As pointed out, two subjects which have different decision sequences may still have the same order-resource assignment outcome. Two subjects with the same decision sequences have the same order-resource assignment outcome. Two subjects which have a the same order-orientation of their decision sequences (say both first process order A, then order B), may still have varying resource-orientation of their decision sequences (either first resource X then Y, or first resource Y, then resource X), resulting in different order-resource assignments and most likely a variance in objective solution quality. The definition of decision sequence and the other constructs used in this chapter are summarized in Table 3.1.

3.2.3 Order and resource-oriented presentation structures

We define presentation structure as the extent to which a display format supports or hinders gathering and computing of certain information items (Larkin and Simon, 1987; Jarvenpaa, 1989; Dunn and Grabski, 2001). Previous literature has studied a variety of presentation structures, such as various forms of tabular displays and of bar diagrams (Jarvenpaa, 1989). To categorize presentation structure, Larkin and Simon (1987) distinguish between the notion of informational and computational equivalence. Consider for example two tabular displays, the first gives the user information on one row at a time, the second gives the user information on one column at a time. They both allow the gathering of the same information, and are thus informationally equivalent. However, they differ in the effort necessary to gather the same piece of information, say information on one row, and are therefore not computationally equivalent.

We distinguish between order-oriented and resource-orientated presentation structures (Kärkkäinen and Holmström, 2002; Kärkkäinen et al. 2004 ; Holmström et al. 2006. Both presentation structures provide functionality for evaluation order-resource assignment choices; in the classification of Larkin and Simon (1987) they are informa-

Table 3.1: Definition of constructs

Construct	Definition	References
Order-orientated versus resource-oriented information systems	As a legacy of paper based information systems, computerized information systems are often resource-oriented. They are built around resources such as storage locations, machines and typically treat products as anonymous entitites. Order-oriented information systems focus on the order or the individual product which is beneficial as orders are captured and controlled individually.	Kärkkäinen et al., 2003b; Kärkkäinen et al., 2004; Holmström et al., 2006
Decision sequence	Order in which an individual selects a series of alternatives constituting a larger task.	Simon, 1955; Payne, 1976; Jarvenpaa, 1989
Order-orientation of a decision sequence	Extent to which the orders in a decision sequence reflect the sequence of orders in the task list.	Simon, 1955; Payne, 1976; Jarvenpaa, 1989
Resource-orientation of a decision sequence	Extent to which the resources in a decision sequence reflect the sequence of resources in the task list.	Simon, 1955; Payne, 1976; Jarvenpaa, 1989
Cognitive style	The way in which subjects make decisions.	Witkin et al., 1971; O'Keefe, 1989; Allinson and Hayes, 1996; Banker and Kauffman, 2004
Time pressure	The time allocated for conducting a task.	Maule and Svenson, 1993; Hwang, 1994
Presentation structure	The extent to which a display format supports or hinders gathering and computing of certain information items.	Larkin and Simon, 1987; Jarvenpaa, 1989; Dunn and Grabski, 2001
Order-oriented presentation structure	Display format which supports comparing of information items related to one order (as opposed to one resource).	Larkin and Simon, 1987; Jarvenpaa, 1989; Dunn and Grabski, 2001
Resource-oriented presentation structure	Display format which supports comparing of information items related to one resource (as opposed to one order).	Larkin and Simon, 1987; Jarvenpaa, 1989; Dunn and Grabski, 2001

tionally equivalent. However, they are not computationally equivalent. In the order-oriented presentation structure each line starts with an order, likewise in the resource-oriented presentation structure each line starts with a resource. In the order-oriented interface it is comparatively easy to examine order-resource combinations for one order. In the resource-oriented interface it is comparatively easy to examine order-resource combinations for one resource.

3.2.4 The effect of the presentation structure on decision sequences

The format in which information is presented to users can influence the way users gather and acquire information (Jarvenpaa, 1989; Lurie and Mason, 2007). Different grouping of interaction items can influence the way users link concepts to each other (Larkin and Simon, 1987). The relative position of the interaction items gives the users cues as to how they are linked, and such links can guide the attention of users (Dunn and Grabski, 2001). After inspecting one item it is easier to follow the graphical link to another item than deliberatively deviating from the graphical recommendation and inspecting some other item. Subjects using a tabular display which structures information based on attributes are likely to gather and proces information in an attribute-oriented manner, and subjects using a tabular display which structures information based on alternatives are likely to gather and process information in an attribute-oriented manner (Bettman and Kakkar, 1977).

While both the order-oriented and the resource-oriented presentation structure allow gathering the same information, they are not computationally equivalent. Having assigned one order to one resource, the attention is guided to the next order in the order-oriented presentation structure. Likewise, having assigned one order to one resource, the attention is guided to the next resource in the resource-oriented presentation structure. Depending on the presentation structure, subjects are more inclined to process either the next order or process the next resource which affects the order and resource-orientation of the decision sequence. This leads us to the following Hypotheses:

Hypothesis 1a: Order-oriented presentation structures elicit order-oriented decision sequences to a greater extent than resource-oriented presentation structures.

Hypothesis 1b: Resource-oriented presentation structures elicit resource-oriented decision sequences to a greater extent than order-oriented presentation structures.

3.2.5 Moderating effects: cognitive style and time pressure

Low and high-analytics differ in the way they make decisions (Witkin et al., 1971). In contrast to low-analytics, high-analytics more easily distill simple figures in complex patterns. If information is presented by visual clues, high-analytics more therefore are able to more easily distinguish the information from the presentation structure. In contrast, for low-analytics it will cost more effort to deviate from the format given by the presentation structure. As a result, the data that enters cognitive information processing of low-analytics is more biased by the structure in which it is presented. Low-analytics are more likely than high analytics to follow the attention management of the presentation structure. We formulate the following Hypotheses:

Hypothesis 2a: Presentation structure affects order-orientation of decision sequences more for low than for high-analytics.

Hypothesis 2b: Presentation structure affects resource-orientation of decision sequences more for low than for high-analytics.

Time pressure can increase task difficulty (Hwang, 1994). Whereas under low time pressure, planners may have time to thoroughly process the data, this processing turns more into a mere reaction under increasing time pressure. Therefore, under time pressure, decision makers are even more likely to do what is easy. For example, decision makers under time pressure do not use all the information available to them (Weenig and Maarleveld, 2002). Likewise, time pressure limits the extent to which decision makers deviate from information processing proposed by the presentation structure. We formulate the following Hypothesis:

Hypothesis 3a: Presentation structure affects order-orientation of decision sequences more as time pressure increases.

Hypothesis 3b: Presentation structure affects resource-orientation of decision sequences more as time pressure increases.

Table 3.2: Planning phases and presentation structures

	low time pressure		high time pressure	
Warm up	order-oriented	resource-oriented	order-oriented	resource-oriented
Warm up	resource-oriented	order-oriented	resource-oriented	order-oriented

3.3 Method

3.3.1 Experimental design

The hypotheses are tested with data collected from a lab experiment (118 undergraduate and graduate students). The experimental variables in the setup are control interface and time pressure resulting in a 2 * 2 factorial design. Cognitive style is a co-variate. We chose for a repeated measures design, collecting data on four cells from each participant. All participants started with a warmup planning phase and then played four different planning phases. There were two different sequences of these four planning phases, also presented in Table 3.2. Participants were randomly assigned to start with either the order-oriented or the resource-oriented presentation structure. The second planning phase was played with the other presentation structure. In the first two phases participants were working under the low time pressure condition. The control interface of the third and fourth phase were the same as the presentation structure of the first and second phase respectively. However, participants worked under the high time pressure condition in these two phases.

For each planning day, participants had to manage a different problem instance. There are two problem instances for the low time pressure and two problem instances for the high time pressure condition. After having collected about half of the observations, we switched the problem instance sets within each time pressure condition so that about half of the participants planned with the order-oriented presentation structure and problem instance 1 under the low time pressure condition. About half of the participants planned with resource-oriented presentation structure and problem instance 1 under low time pressure condition. Problem instances differ by orders and the starting positions of the trucks. Table 3.3 gives an overview of the problem instances. The last column in Table 3.3 describes the *sequence of alert messages*. Alert messages are issued 10 minutes before the delivery time by a cell related to that order turning red. Orders

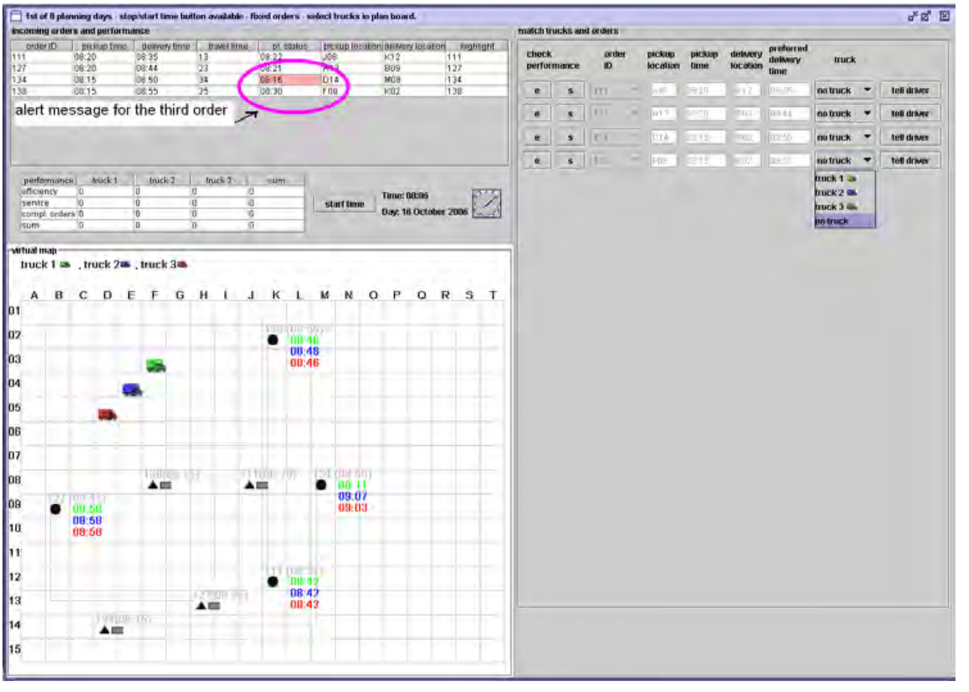


Figure 3.2: The lab experiment software with an order-oriented presentation structure and an alert message for the third order

have different delivery times and for 2 problem instances the sequence of alerts coincides with the sequence of orders appearing on screen. For these problem instances the top cell which is related to the first order can turn red, then the second, then the third and the fourth. For example problems instance 2 this is not the case. At 8:20 both the first and the last cell can turn red, and at 8:30 the second and third cell can turn red. The *order-orientation of the alert sequence* describes the extent to which the sequence of alert messages coincides with the sequence of orders in the task list.

3.3.2 Decision task

Participants assumed the role of a planner in a transportation company, just like in the previous chapter. On a given planning day 4 orders arrive and three trucks are available

Table 3.3: Problem instances for low and high time pressure

order ID	order arrival time	pick up location	pick up time	delivery location	delivery time	sequence warning messages [a]
low time pressure						
problem instance 1, starting positions truck: F03, E04, D05 (order-orientation of the alert sequence:[b] 4)						
111	08:01	J08	08:20	K12	08:35	1st (8:25)
127	08:02	H13	08:20	B09	08:44	2nd (8:34)
134	08:03	D14	08:15	M08	08:50	3rd (8:40)
138	08:04	F08	08:15	K02	08:55	4th (8:45)
problem instance 2, starting positions trucks: K02, M02, O02 (order-orientation of the alert sequence:[b] 2)						
123	08:01	H08	08:15	E11	08:30	1st (8:20)
127	08:02	D07	08:20	N09	08:40	2nd (8:30)
145	08:03	J06	08:20	M12	08:40	2nd (8:30)
152	08:04	F14	08:15	I12	08:30	1st (8:20)
high time pressure						
problem instance 3, starting positions trucks: H10, J12, L14 (order-orientation of the alert sequence:[b] 3)						
143	08:01	Q10	08:25	P06	08:45	2nd (8:35)
167	08:02	O03	08:25	L02	08:35	1st (8:25)
188	08:03	D07	08:25	I14	08:50	3rd (8:40)
192	08:04	K10	08:25	G05	08:50	3rd (8:40)
problem instance 4, starting positions trucks: J04, H06, F08 (order-orientation of the alert sequence:[b] 4)						
101	08:02	G03	08:25	E01	08:30	1st (8:20)
108	08:03	B02	08:25	A05	08:35	2nd (8:25)
121	08:04	O07	08:25	K11	08:45	3rd (8:35)
145	08:05	F12	08:25	J08	08:50	4th (8:40)

[a] Alert messages are issued 10 minutes before the delivery time by changing the background color of the respective cell in the order income table from white to red.

[b] Extent to the sequence of alert messages coincides with the sequence of orders in the task list

for executing them. The participants had to make the following decision: which truck should execute which order? Planning performance was measured by two components: efficiency and service. Efficiency was measured as the distance that trucks drive empty, and service was measured by multiplying the total number of late minutes of order deliveries by 30. Participants could solicit information about performance consequence of order-truck combinations before they had to make the final decision.

3.3.3 Experimental conditions

Two variables were manipulated: presentation structure and time pressure. In the order-oriented presentation structure, orders are fixed and cannot be changed. For each order the user can select a truck from a list (view Figure 3.3). In the resource-oriented presentation structure, the truck is fixed and orders can be selected from a list (view Figure 3.3). In the low time pressure condition, participants were given a button to stop or start the running time. Under high time pressure conditions, no such button was available.

3.3.4 Measurement

We measure the order-orientation of a decision sequence by the variable order-assign orientation based on previous research (Payne, 1976; Jarvenpaa, 1989). Order-assign orientation is defined as number of instances in which the nth and the (n+1)th order-resource-combination in the decision sequence contain orders that are subsequent orders in the task list. Likewise we measure the resource-orientation of a decision sequence by the variable resource-assign orientation, which is defined as the number of instances in which the nth and the (n+1)th order-resource-combination contain resources that are subsequent resources in the task list, whereas the last resource is followed by the first resource. Cognitive style was measured with the same test as in the previous chapter.

3.3.5 Descriptive statistics

Table 3.5 presents descriptive statistics describing the lab experiment. Under each time pressure condition high-analytics have a higher score than low-analytics. Both groups

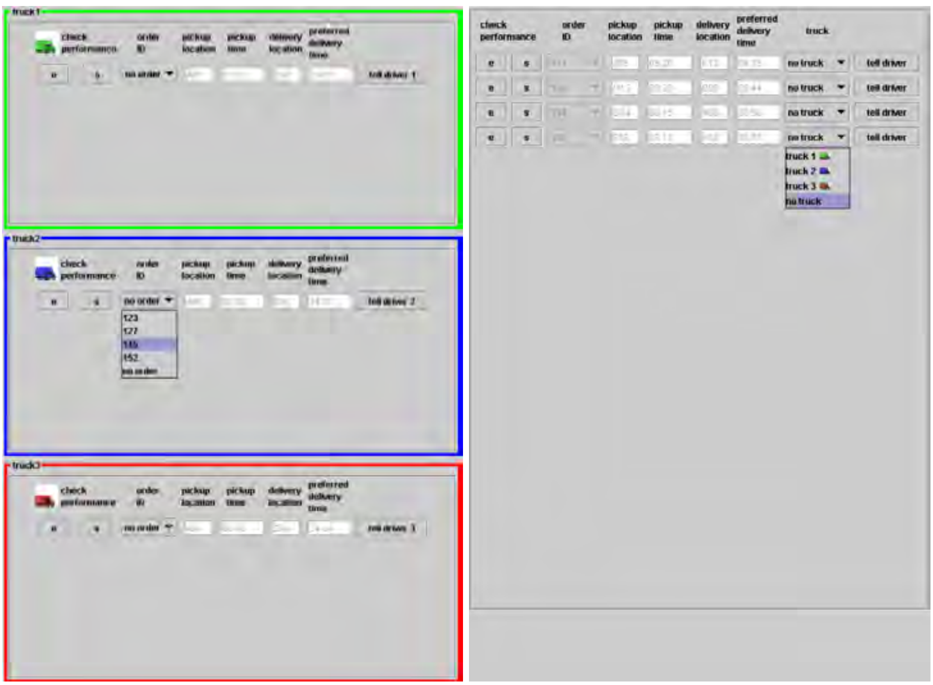


Figure 3.3: Resource-oriented (left) and order-oriented (right) presentation structures

Table 3.4: Objective measurement scales

Variable	Measurement
Efficiency	- Distance traveled empty
Service	- Number of late minutes
Total score	(3000 * Number of completed orders) + Efficiency + 50 * Service
Duration real time	Number of minutes that the whole planning phase took in terms of real time
Simulation time	Game time which was 60 times faster than real time. In low time pressure participants could pause the game with a button.
Cognitive Style	Score from the Hidden Figures Test, a Gottschaldt-Thurstone adoption of the Embedded Figures Test (French et al., 1963; Feldberg, 2006).
Order-assign orientation	Number of instances in which the nth and the (n+1)th order-resource-combination contain orders that are subsequent orders in the task list.
Alert-assign orientation	Number of instances in which the nth and the (n+1)th order-resource-combination contain orders that are subsequent orders in the sequence in which alerts for the respective orders are issued (for post hoc analysis).
Resource-assign orientation	Number of instances in which the nth and the (n+1)th order-resource-combination contain resources that are subsequent resources in the task list, whereas the last resource is followed by the first resource.

Table 3.5: Descriptive statistics

	Mean			
	low-analytics		high-analytics	
Time pressure	low	high	low	high
Score	5905	3859	6830	5124
Duration real time (min.)	5.08	1.84	4.47	1.64
Duration simulated time (min.)	19.19	54.98	15.07	45.55

received higher scores under low time pressure than under high time pressure. Under low time pressure low-analytics needed 5.08 minutes real-time to finish a planning phase, high-analytics only 4.47 minutes. Under high time pressure both groups needed less than 2 minutes. This indicates that subjects were using the additional time they received during low time pressure. In terms of simulated minutes, subjects needed less than 20 minutes during low time pressure and more than 45 minutes during high time pressure. This indicates that subjects made good use of the option to pause time during low time pressure planning phases.

Table 3.6 and Figure 3.4 present frequency statistics including all 472 observations on how often which order in the task list was processed when. If subjects randomly select which of the orders they process first, each of the four values in Table 3.4 should have a value around 25%. However, the data shows a certain pattern. The first order in the task list was usually the one processed first (67.37%). The second order to be processed was most often the second order in the task list (58.26%) and the third order to be processed was most often the third order in the task list (60.59%). This pattern of using the i-th order in the i-th assignment decision is depicted graphically by the diagonal line of high bars in Figure 3.4.

We computed similar statistics for resources. Table 3.7 and Figure 3.5 present how often which truck in the task list was processed when. Remember that subjects could assign the same truck several times. We can identify a similar pattern as for orders. In the first assignment the first truck was chosen most often (71.82%). In the second assignment, the second truck was chosen most often (58.26%). In the third assignment, the third truck was chosen more often than other trucks (53.6%) and in the fourth and last assignment, the first truck was chosen most often (41.53%). The pattern of using the i-th truck in the i-th assignment decision is depicted graphically by the diagonal line

Table 3.6: Frequency of which orders are processed when

	Position in decision sequence			
Position in task list	first	second	third	fourth
first order	67.37	19.49	9.11	4.03
second order	15.04	58.26	11.02	15.68
third order	9.32	11.86	60.59	18.22
fourth order	8.26	10.38	19.28	62.08

Table 3.7: Frequency of which trucks are processed when

	Position in decision sequence			
Position in task list	first	second	third	fourth
first truck	71.82	22.03	19.92	41.53
second truck	12.08	58.26	26.48	31.14
third truck	16.1	19.7	53.6	27.33

of high bars in Figure 3.5. Comparing the figures of for orders and resources (Figures 3.4 and 3.5) suggests that the pattern of the i-th order or resource in the i-th assignment decision is less pronounced for resources than it is for orders.

Table 3.8 gives an overview on the variables order-assign orientation and resource-assign orientation. If a subject processes all orders in the sequence as they are presented in the task list, the order-assign orientation variable has the value of 3. This is the case for 45.97% of all 472 observed planning phases. In contrast, subjects have an resource-assign orientation of 3 in only 30.30% of the cases.

Table 3.8: Frequency of order-assign orientation and resource-assign orientation

	0	1	2	3
order-assign orientation	76 (16.10%)	122 (25.85%)	57 (12.08%)	217 (45.97%)
resource-assign orientation	108 (22.88%)	56 (11.86%)	165 (34.96%)	143 (30.30%)

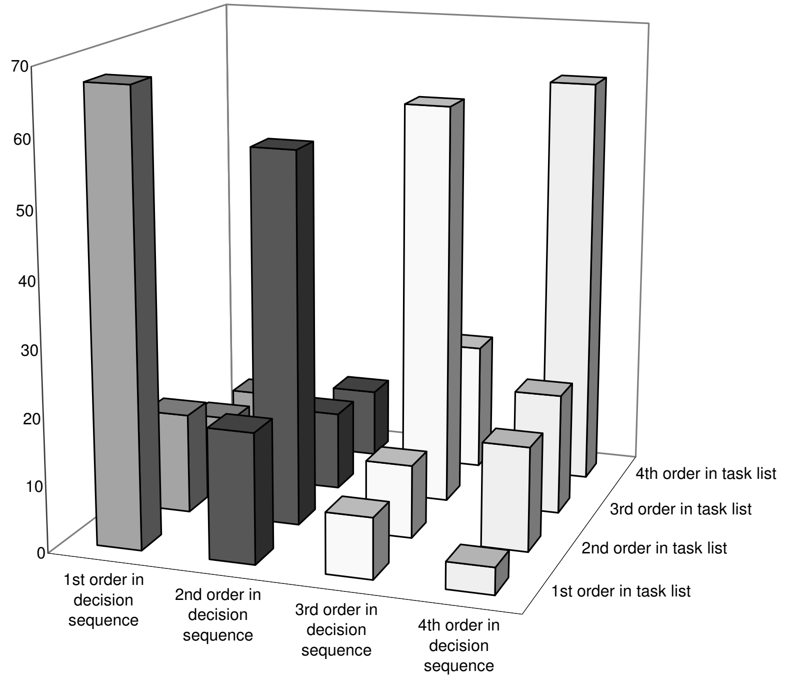


Figure 3.4: Frequency of which orders in task list are processed when

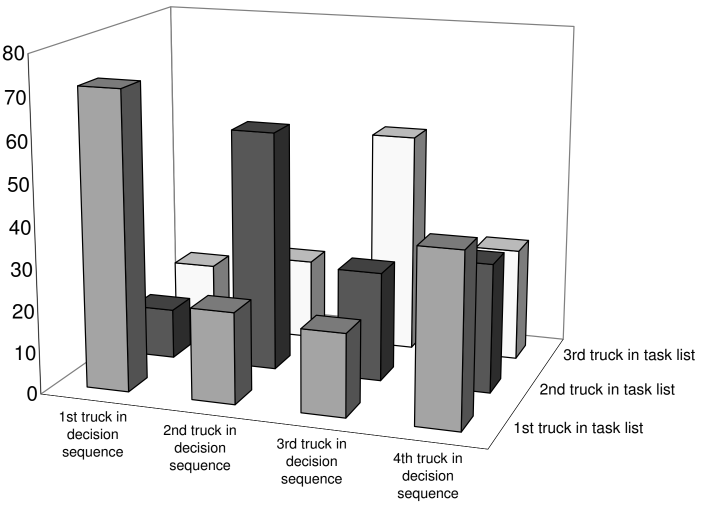


Figure 3.5: Frequency of which trucks in task list are processed when

Basic model

We test our model following the approach of van Bruggen et al. (1998) which examine performance impact of Marketing DSS and the moderating effect of cognitive style and time pressure. The following Equation, which we also refer to as the restricted model, is used to test the effects of presentation structure, cognitive style and time pressure and their interactions:

$$\begin{aligned} DV_{it} = \ & \alpha_0 + \alpha_1 PSTR_t + \alpha_2 TIPR_t + \alpha_3 COGN_i + \alpha_4 PSTR_t * TIPR_t + \\ & \alpha_5 PSTR_t * COGN_i + sequence_t + problem\ instance\ set_t + e_{it} \end{aligned} \tag{3.1}$$

In order to conduct the goodness of fit comparison proposed by Hilbe (2007) we also specify the full model:

$$\begin{aligned} DV_{it} = \ & \alpha_0 + \alpha_1 PSTR_t + \alpha_2 TIPR_t + \alpha_3 COGN_i + \\ & \alpha_4 PSTR_t * TIPR_t + \alpha_5 PSTR_t * COGN_t + \alpha_6 COGN_t * TIPR_t + \\ & \alpha_7 PSTR_t * COGN_i * TIPR_t + sequence_t + problem\ instance\ set_t + e_{it} \end{aligned} \tag{3.2}$$

where *PSTR* is the orientation of the presentation structure, *TIPR* refers to the presence or absence of time pressure, and *COGN* refers to the cognitive style of the individual participant. *Sequence* is a dummy variable indicating whether participants started with order or with resource-oriented presentation structure. *Problem instance set* refers

Table 3.9: Results for order-assign orientation

		restricted model		full model	
Source of Variation	DF	z-score	Sig.	z-score	Sig.
presentation structure	1	-12.44	< 0.0001	- 12.52	$< .0001$
cognitive style	1	0.12	0.4778	-2.88	0.0755
presentation structure * cognitive style	1	2.72	0.0870	4.70	0.0094
time pressure	1	2.88	0.0752	2.80	0.0814
presentation structure * time pressure	1	3.02	0.0646	3.18	0.0557
cognitive style * time pressure	1			4.32	0.0156
presentation structure * cognitive style * time pressure	1			-3.52	0.0396
sequence	1	1.42	0.2381	1.34	0.2504
problem instance set	1	1.44	0.2354	1.44	0.2347
one-tailed significances, standardized coefficients					
-2 Res Log Likelihood		-556.2304		-554.1559	

to the incoming orders as presented in Table 3.3. *DV* refers to the dependent variable and can be either *order-assign orientation* or *resource assign-orientation*.

As the frequency statistics in Table 3.8 show, are both of our dependent variables, *order-assign orientation* and *resource-assign orientation*, not normally distributed Therefore we test our hypotheses with Proc Genmod a procedure that allows formulation of general linear models and ordinal dependent variables (SAS Institute, 2004, p. 79). As with Proc Mixed we can model known explanatory variables separately from the correlation between observations stemming from one participant.

3.4 Discussion of results

3.4.1 Order-orientation of the decision sequence

Our first hypotheses state that presentation structure influences order-orientation and resource-orientation of decision sequences. Based on the approach suggested by Hilbe (2007) we assess model fit by comparing the restricted model (specified in Equation 3.1) with the full model (specified in Equation 3.2). Results from both models are presented in Table 3.9. The full model has a significant three way interaction effect, and therefore we will use this one in our further analysis.

The results presented in Table 3.9 show a significant three way interaction (z-score = -3.52, p = 0.0396). Having a three way interaction indicates that the extent to which one of the three variables (presentation structure, cognitive style, time pressure) influences the dependent variable depends on the a combination of the other two. In our data we have four cognitive style and time pressure combinations (low analytics under low time pressure, high analytics under low time pressure, low analytics under high time pressure and high analytics under high time pressure) and for each two different presentation structures. The mean *order-assign orientation* for each of the resulting eight means are presented in Table 3.10 and in Figure 3.6. Our first observation is that for each of the four cognitive style and time pressure combinations, *order-assign orientation* is higher for decision making with order-orientated presentation structure than with resource-oriented presentation structure. Apparently, the effect of presentation structure in all four cognitive style and time pressure combinations is of the same direction: an order-oriented presentation structure leads to higher *order-assign orientation* of the decision sequence than a resource-oriented presentation structure. This supports Hypothesis 1a.

We examine if the effect of presentation structure in all four cognitive style and time pressure combinations is of a varying extent. Table 3.10 and Figure 3.7 show the difference between order and resource-oriented presentation structure for each of the four cognitive style and time pressure combinations. The data suggest that time pressure has a different impact on *order-assign orientation* of low and high-analytics. Time pressure decreases the difference in impact between both presentation structures on *order-assign orientation* of low-analytics. In contrast, time pressure increases the difference in impact between both presentation structures on *order-assign orientation* of high-analytics.

The data seem to suggest that as time pressure increases, high-analytics become more subject to manipulation by presentation structure than low-analytics. This is not in accordance with our Hypothesis 2a, which states that *order-assign orientation* of decision sequences of low-analytics are more subject to presentation structure than of high-analytics. Post hoc analysis instead suggests another expectation: as time pressure increases, low-analytics become subject to another form of manipulation. Remember that the problem instances differ in the sequence in which alert messages are issued (presented in Table 3.3). For problem instances 1 and 4, these alerts are in a sequence

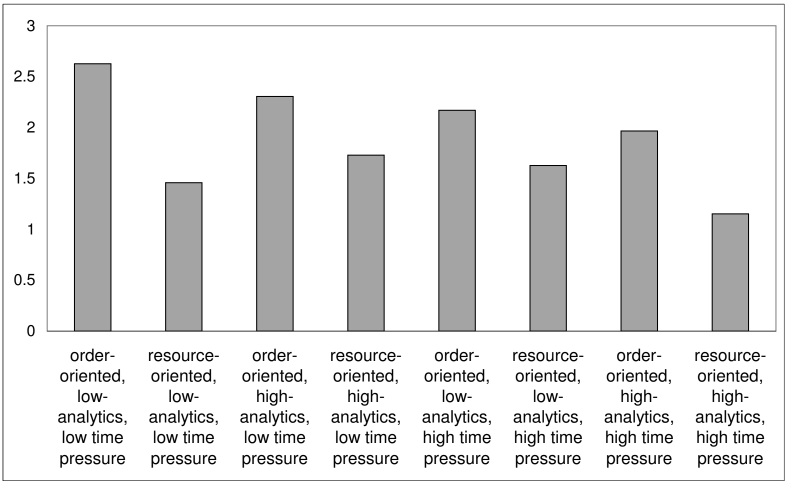
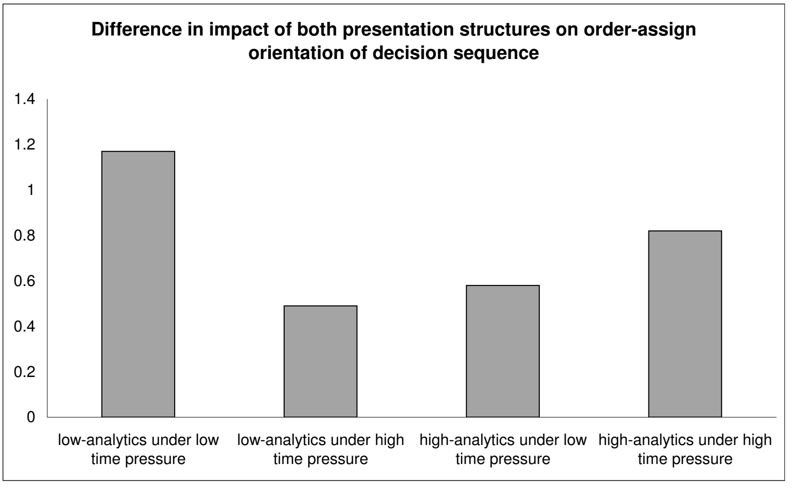


Figure 3.6: Average order-assign orientation for each of the eight combinations of cognitive style, time pressure and presentation structure

Table 3.10: Means for order-assign orientation and alert-assign orientation

	Order-assign orientation			
	low time pressure		high time pressure	
	low-analytics	high-analytics	low-analytics	high-analytics
Presentation structure				
order-oriented	2.63	2.31	2.12	1.97
resource-oriented	1.46	1.73	1.63	1.15
difference	1.17	0.58	0.49	0.82
	Alert-assign orientation			
	low time pressure		high time pressure	
	low-analytics	high-analytics	low-analytics	high-analytics
	1.53	1.45	1.58	1.25



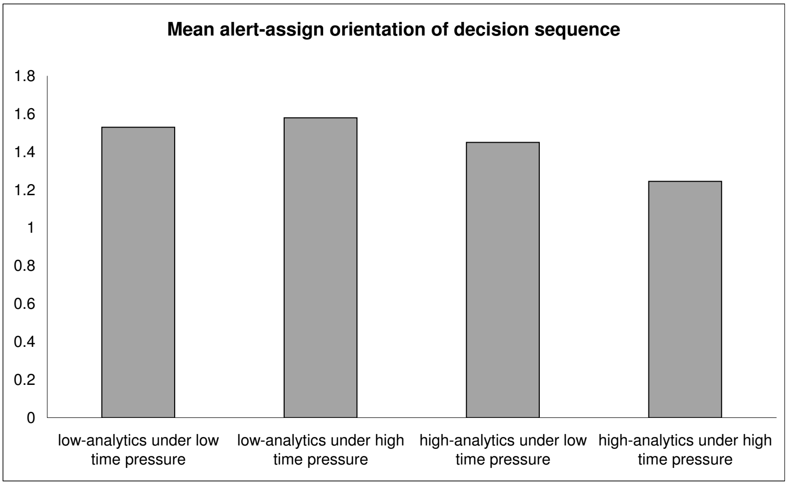


Figure 3.7: Impact of presentation structure and alert sequence on all four combinations of cognitive style and time pressure

completely reflecting the sequence of orders in the task list. That is, the first order in the task list is the first order to send an alert message, the second order in the task list sends the second alert message and so forth. In contrast, for problem instance 2, the first alert messages are sent by the first and the last order at the same time. For problem instance 3, the first alert message is sent by the second order in the task list. Similar to the calculation of *order-assign orientation* we calculate the variable *alert-assign orientation* which reflects the extent to which the decision sequence resembles the sequence of alert messages. We define *alert-assign orientation* as the number of instances in which the nth and the (n+1)th order-resource-combination contain orders that are subsequent orders in the sequence in which alerts for the respective orders are issued. Table 3.10 and Figure 3.7 present the mean *alert-assign orientation* for each of the four cognitive style and time pressure combinations. The data show that the alert-assign orientation slightly increases for low-analytics as time pressure increases (mean low time pressure = 1.53 and mean high time pressure = 1.58). For high-analytics the *alert-assign orientation* decreases with time pressure (mean low time pressure = 1.45 and mean high time pressure = 1.25). Comparing the impact of varying presentation structure on decision sequences (Figure 3.7, graphic above) with the mean *alert-assign orientation* (Figure 3.7, graphic below) illustrates our argumentation: with increasing time pressure, the impact presentation structure decreases for low-analytics and the impact of alert messages on decision sequence increases. For, high analytics it is the other way around. With increasing time pressure, the impact presentation structure increases for high-analytics and the impact of alert messages on decision sequence decreases.

We test the impact of presentation structure, cognitive style and time pressure on the *alert-assign orientation* in the same manner as for the *order-assign orientation*. The results of the restricted model (specified in Equation 3.1) and the full model (specified in Equation 3.2) are presented in Table 3.11. As there is not significant three way interaction of the full model, and the goodness of fit measures are virtually similar, we use the results of the restricted model for our analysis.

The results regarding *alert-assign orientation* suggest a significant impact of presentation structure (z-score = -7.64, $p < 0.0001$), and problem instances (z-score = - 5.98, p=0.0014). The frequency statistics presented in Table 3.12 allow identifying the pattern for the significant effects. *Alert-assign orientation* is higher in order-oriented presentation structures than in resource-oriented presentation structures, presumably because of the relative ease of finding orders on in the presentation structure after the alert has been

Table 3.11: Results for alert-assign orientation

		restricted model		full model	
Source of Variation	DF	z-score	Sig.	z-score	Sig.
presentation structure	1	-7.64	< 0.0001	7.62	< 0.0001
cognitive style	1	3.24	0.0512	0.60	0.3839
presentation structure * cognitive style	1	-1.52	0.2237	-.22	0.4580
time pressure	1	1.92	0.1696	1.96	0.1626
presentation structure * time pressure	1	-0.20	0.4589	-.24	0.4516
cognitive style * time pressure	1			3.06	0.0631
presentation structure*cognitive style * time pressure	1			-2.3	0.1251
sequence	1	0.38	0.4255	0.36	0.4284
problem instances set	1	-5.98	0.0014	-5.94	0.0015
one-tailed significances, standardized coefficients					
-2 Res Log Likelihood		-551.8660		-550.9068	

issued. The frequency statistics provided in Table 3.12 show that decision sequences are more often in line with the sequence of orders in the task list if the alert sequence of the problem instance does not deviate from the sequence of orders in the task list.

Due to the confounding effects of alert messages on *order-assign orientation* of the decision sequence we cannot draw clear conclusions if our Hypotheses 2a and 3a are being supported. The data suggests that as time pressure increases, *order-assign orientation* of the decision sequence of low-analytics becomes influenced by alerts appearing on screen. In contrast, as time pressure increases, the *order-assign orientation* of the decision sequence of high-analytics becomes more influenced by the impact of presentation structure.

3.4.2 Resource-orientation of the decision sequence

Hypotheses 1b, 2b and 3b state that the resource-orientation of decision sequences can be influenced by presentation structure and that this influence increases for decision makers with a low-analytical rather than a high-analytical cognitive style and decision makers under high rather than low time pressure. We test the result for the variable *resource-assign orientation* in the same was as for the variable *order-assign orientation*. The

Table 3.12: Frequency of alert-assign orientation

	0	1	2	3
all observations	107 (22.67%)	201 (42.58%)	26 (5.51%)	138 (29.24%)
		presentation structure		
order-oriented	31 (13.14%)	99 (41.95%)	13 (5.51%)	93 (39.41%)
resource-oriented	76 (32.20%)	102 (43.22%)	13 (5.51%)	45 (19.07%)
		problem instances		
			low time pressure	
problem instance 1 (4)[a]	7 (5.93%)	35 (29.66%)	7 (5.93%)	69 (58.47%)
problem instance 2 (2)[a]	40 (33.90%)	69 (58.47%)	7 (5.93%)	2 (1.69%)
			high time pressure	
problem instance 3 (3)[a]	45 (38.14%)	57 (48.31%)	11 (9.32%)	5 (4.24%)
problem instance 4 (4)[a]	15 (12.71%)	40 (33.90%)	1 (0.85%)	62 (52.54%)

[a] number in parentheses refers to the extent that alerts of the problem instance are issued in line with sequence of orders in the task list

Table 3.13: Results for resource-assign orientation

		restricted model		full model	
Source of Variation	DF	z-score	Sig.	z-score	Sig.
presentation structure	1	2.52	0.1047	2.48	0.1081
cognitive style	1	-1.66	0.2038	-2.58	0.0991
presentation structure * cognitive style	1	1.64	0.2063	0.96	0.3165
time pressure	1	0.02	0.4978	-0.04	0.4909
presentation structure * time pressure	1	2.24	0.1308	-2.24	0.1314
cognitive style * time pressure	1			1.98	0.1604
presentation structure*cognitive style * time pressure	1			1.40	0.4708
sequence	1	0.16	0.4684	0.18	0.4658
problem instances set	1	1.62	0.2058	-1.68	0.1991
one-tailed significances, standardized coefficients					
-2 Res Log Likelihood		-620.9071		-619.8870	

results of the restricted model (specified in Equation 3.1) and the full model (specified in Equation 3.2) are presented in Table 3.13. We observe that there are no significant effects of presentation structure, cognitive style, time pressure or any of their interaction terms. Therefore the data does not support Hypotheses 1b, 2b, and 3b. However, the descriptive statistics in Table 3.7 suggest that in principle subjects are inclined to process the first resource first, then the second, and then the third, and after that they choose the first resource for the fourth assignment.

To summarize, presentation structure can influence the sequence in which decision makers process orders, but not the sequence in which they process resources. The sequence of which orders are processed can be influenced both by the presentation structure and the alert messages that appear on screen. An order-oriented presentation structure leads to a processing that is more in accordance with sequence of orders in the task list than a resource-oriented presentation structure. In the absence of alert messages subjects are more likely to process orders as they are presented in the task list.

3.5 Conclusions

Based on data from 118 participants of a lab experiment, we found that both alert messages and presentation structure influence the decision sequence of subjects. As time pressure increases, the influence of alert messages on the decision sequence of low analytics increases, while the decision sequences of high-analytics are increasingly influenced by presentation structure.

This study shows that the presentation structure may influence decision makers when they assign orders to resources. Strictly speaking this does not have to deteriorate objective solution quality. However, it can, namely, if a decision maker chooses the best available resource for each order, then the available resources become fewer with each taken order-resource selection. For example, the overall optimal order-resource assignment may assign the first resource to the second order. However, due to sequential processing a decision maker may already have committed this resource to the first order. This study suggests a new functionality that planning software may provide. In addition to sorting orders and resources by such arbitrary criteria as order number, or client name, they may also be ”sorted by optimality”.

The suggested sorting by optimality functionality presents data in such a way that decision makers which follow the most efficient information processing approach, basically assigning the i-th order to the i-th resource, will have high objective solution quality. Decision sequences can best be predicted for displays with an order-oriented presentation structure, and in the absence of disturbing alert messages. However, further forms of presenting data by optimality may be possible. Lurie and Mason (2007) provide a comprehensive overview of literature examining the effect of various display formats for information processing. Further research may study these effects specifically for a logistics task so that software designers know which display formats can predict which information processing.

In this chapter, data collected from students is used to test theory aimed at experts in decision making. While students and experts in decision making do not necessarily differ (Remus, 1986), the findings should be taken with care. The experience that planners have can give them a stronger sense of decision making direction which can not as easily be influenced by the interface. Decision making in practice is not as well defined as in a laboratory setting. There are many influences which may superimpose the effect that we have discussed here. Planners may choose to process orders by factors such as tardiness, importance of clients, but also factors rather distant to objective solution quality such as drivers having lunch together (Hill, 1982). Planners in practice may also have a decision making approach which they are so used to that variance in presentation structure is not sufficient to influence their decision making. However, given the low adoption rates of OR-based DSS in practice, buyers and vendors of planning software may consider the functionality to sort by optimality.

An unintended finding of this chapter is that the sequence of alert messages can influence the information processing of planners. In hindsight, this finding is not so surprising as salient user elements can guide the attention and therefore information processing and gathering of users (Jarvenpaa, 1990; Lurie and Mason, 2007). This finding has an important implication for the role of monitoring agents in planning processes. Agents can monitor data streams and continuously assess execution situation (Banker and Kauffman, 2004). Human planners benefit by not having to carry out this monotonous task herself. However, this benefit might come at a price. Our results indicate that monitoring agents can influence order processing. It is possible that this influence is not always welcome. The agent might disturb the planner in an important cognitive process, e.g. a telephone conversation to change orders of a highly profitable customer. It is important to conduct such studies with a focus on planning tasks in business settings. Unlike, say, for fire brigades, warnings are not equally important in a business setting. A planner that concentrates on a preferred customer should not be disturbed by an automatically generated warning that an order that is hardly profitable will be delivered five minutes late. Further research is necessary to establish which forms of intervention are beneficial under which situation. Cognitive style can help in predicting to which stimulus people are likely to respond. The most dominant definition of cognitive style in decision support literature is the one proposed by Witkin (1971). However, the set of cognitive style definitions is so large that even different typologies exist (Hayes and Allinson, 1994). Further research might benefit from studying other cognitive styles.

OR algorithms can contribute to decision making not only by calculating the optimal solution, but also by summarizing solution space in a meaningful way. For example, in a sequential processing approach committing one resource to one order renders entire parts of solution space inaccessible. Planners may benefit from messages that inform them that these parts contain many near optimal solutions. OR algorithms may also be used to find not only optimal solutions, but neighborhoods of optimal solutions, whereas distance between solutions is defined by the computation effort necessary for the planner to gather and compute information for comparing one solution to another.

Chapter 4

Isolated versus collaborative use of decision support systems in transport planning

4.1 Introduction

While the use of OR-based DSS can improve solution quality for abstract OR problems considerably, they seem to have little use for practitioners. Little is known why that is so (Bendoly et al., 2006). The way information systems are used may have considerable impact on realizing the potential they offer (Goodhue, 1995; Devaraj and Kohli, 2003). If we know what usage increases performance in a real-life setting, we may find more effective ways of introducing OR to the planning process.

Planners can make use of DSS to explore solution space and improve solution quality for the orders and resources under their responsibility (Anthonisse et al., 1988). We label this use as *use of isolated optimization*. A planner may use the insights from exploring solution space also to contact planners who have other orders and resources under their responsibility, and discuss exchanges that can improve solution quality for both sets. We label this as *use of collaborative optimization*. Collaborative optimization has a larger solution space than isolated optimization. Remember that we define the extent to which planners depend on planners in the same or in other companies for carrying out the planning task as *planner-interdependence* (Thompson, 1967; Aiken and Hage, 1968;

Jermier and Berkes, 1979; Morris and Steers, 1980; Price, 1997) and use this construct as a proxy for the extent of exchanging orders and resources between planners in the same or in different companies. While benefits of such collaborative problem solving are well documented for decision making on a strategic level (Chen and Paulraj, 2004), the benefits of human problem solving skills are often ignored for decision making on the operative level (Boudreau et al., 2003).

We compare the performance effect of two different uses of DSS: (1) *use of isolated optimization* and (2) *use of collaborative optimization*. We model the *use for isolated optimization* as a direct effect of intensity of DSS use on planning satisfaction. *Use of collaborative optimization* is modeled as an indirect effect consisting of two parts: the impact of intensity of DSS usage on planner-interdependence, and the impact of planner-interdependence on planning satisfaction. In other words, the *use of collaborative optimization* is modeled as the mediating effect of planner-interdependence on the direct effect *use of isolated optimization*. The research question we examine is: what is the impact of the intensity of use of DSS on planning satisfaction and to what extent is this effect mediated by planner-interdependence? By examining the extent of the mediating effect we can examine which usage is more important and to what extent (Baron and Kenny, 1986). The same analysis will also provide insight into the role of collaborative problem solving for transport planning.

4.2 Framework and hypotheses development

Figure 4.1 gives a graphical representation of our conceptual model. It distinguishes two uses of DSS: (1) *use of isolated optimization* (Hypothesis 1); and (2) *use of collaborative optimization* (Hypotheses 2 and 3).

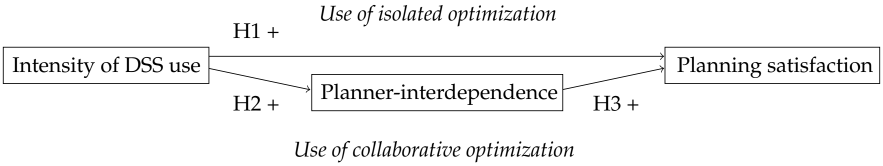


Figure 4.1: Use of isolated versus use of collaborative optimization

4.2.1 DSS for transportation

Low adoption rates of OR tools indicate that there may be other software packages present that assist planning processes. For example, email exchange with customers (Vickery et al., 2004), and Electronic Data Interchange (EDI) tools (Stefansson, 2002), may provide overviews of unprocessed orders that can provide rudimentary assistance. The decision maker does not need to spend cognitive resources on keeping the data in his working memory and can use the freed up resources on for example more demanding aspects of the problem (Baddely, 1992; Lerch and Harter, 2001). Sophisticated monitoring tools also provide status reports and overviews on orders and resources (Florence and Queree, 1993; McFarlane and Sheffi, 2003; Kärkkäinen et al., 2004). In addition, they may provide features for evaluating planning alternatives such as based on historical accounting data regarding profit, service or other performance indicators (Krauth et al., 2005). Some sophisticated monitoring systems provide spatial presentations of the execution status, for example a virtual map indicating location of trucks and client sites, which planners may use for planning (Crossland et al., 1995; Tarantilis and Kiranoudis, 2002; Applegate et al., 2007). Also some Internet based tools may provide support, for example, by delivering traffic information or providing tools for calculating travel distance (Golob and Regan, 2002).

The kind of DSS used for assisting the planning process may not play such an important role as the way it is used (Goodhue, 1995; Devaraj and Kohli, 2003). Devaraj and Kohli (2003) arrive at this conclusion based on examining data of a three-year period including various measures for usage and technology. In a similar study, Devaraj et al. (2007) find no direct effect of eBusiness technologies on performance, but only an indirect performance effect: these technologies increase supplier integration, which in turn increases performance.

For transport planning, usage of information systems may vary in intensity. If a planner takes 100 decisions a day and they are carried out in a way assisted by a DSS, intensity of usage is high. If only 50% of decisions are assisted by DSS, intensity of DSS usage is low. The variance in intensity of DSS use can be informed by the degree to which specific decisions are perceived as routine or not. For routine processing, planners may let OR based DSS do the planning, in the sense of automated decision making. For event handling and special customer requests, human planners may prefer to find solutions manually.

In addition to varying intensity of usage, planners may also use DSS for different purposes. Some planners may use functionality to compare two alternatives in terms of efficiency. Other planners may mainly be interested in functionality for comparing punctuality. This may depend on the skill level of the user regarding both planning experience and background as well as software proficiency in general. The relative importance of DSS functionality in the planning task may also depend on the particular business model of the transport company. We refer for different DSS usages for different purposes as functionalities. We distinguish eight different functionalities of DSS extending on the three phases identified by Lerch and Harter (2001): *alternative generation*, *alternative evaluation* and *alternative selection*. Generation of alternatives refers to establishing a set of solution alternatives that can then be considered in the following step of evaluation. In a transportation context, the phase of alternative generation may be supported by electronic lists with information on routes, orders or drivers. Evaluation refers to comparing alternatives in terms of one or several performance indicators. Planners in transportation might be interested in comparing or sorting alternatives on efficiency, punctuality, profit as well as travel and rest times. In the third phase, selection, a planner chooses the definite decision, such as which order is to be executed by which truck. We define intensity of DSS use as the extent to which an unspecified software is used for a specified phase of the decision making process: generation, evaluation, and selection of alternatives. The definition of intensity of DSS use and the other constructs used in this chapter are summarized in Table 4.1.

Table 4.1: Definition of constructs

Construct	Definition	References
Intensity of DSS use	Extent to which software is used for a specified phase of the decision making process: generation, evaluation, and selection of alternatives.	Lerch and Harter, 2001; Ahmad and Schroeder, 2001
Planner-interdependence	Extent to which planners depend on planners in the same or in other companies for carrying out the planning task.	Thompson, 1967; Aiken and Hage, 1968; Jermier and Berkes, 1979; Morris and Steers, 1980; Price, 1997
Planning satisfaction	Satisfaction with decisions of the planning department.	Sanders and Courtney, 1985; Lilien et al., 2004

4.2.2 Use of isolated optimization

Planning satisfaction

Objective solution quality, reflected in measures such as resource utilization or tardiness, is one way to measure performance of a planning department. However, it does not always reflect all relevant performance aspects. Objective solution quality of the final plan neglects factors related to decision making process such as decision making speed. In practice, quality of a plan may also depend on the extent to which possible disturbances are accounted for (Gary et al., 1995; Powell et al., 2000; Giaglis et al., 2004; Frei, 2006). Already now 40% of orders are not executed the way they were planned (Calisti et al., 2005). To capture all these aspects of planning performance we use a measure for performance that is broader than objective solution quality: planning satisfaction, which we adapted from decision satisfaction and which is defined as satisfaction with the decisions of the planning department (Sanders and Courtney, 1985; Lilien et al., 2004). Also, our study is motivated by low adoption rates of OR-based DSS and increases in objective solution quality are not always decisive for increasing use of DSS (Todd and Bensabat, 1999). Instead, the extent to users perceive that a system will increase their performance in an organizational context is an adoption antecedent in many contexts (Davis, 1989; Chau and Hu, 2002; Amoako-Gyampah and Salam, 2004; Shih, 2004).

Impact of intensity of DSS use on planning satisfaction

In the use of isolated optimization, planners use DSS to improve the plans for the orders and resources under their responsibility. This may include tasks such as entering planning data to the system, making a decision and then communicating it to drivers and customers. Planners can use DSS for exploring solution space (Anthonisse et al., 1988). The more often planners make use of DSS for their decisions, instead of not using any system at all, the more often they will benefit at least from rudimentary form of support, namely storage of information thereby freeing up working memory (Baddely, 1992; Lerch and Harter, 2001). This can be beneficial to both the decision speed and the solution quality. Also, the more often planners use DSS for evaluating or selecting alternatives the more often they will have benefited from functionality that can take more data into account and makes more use of sophisticated models, which also are both likely to improve solution quality. This leads us to our first Hypothesis:

H 1: Increased intensity of DSS use increases planning satisfaction.

4.2.3 Use of collaborative optimization

Planner-interdependence

Planners may work together with planners from the same or from other companies, in order to outsource orders or lend resources. Planners sometimes depend on other planners for their work to varying degrees and this variance is referred to as task interdependence (Thompson, 1967; Aiken and Hage, 1968; Jermier and Berkes, 1979; Morris and Steers, 1980; Price, 1997). The different levels of interdependence can be categorized as follows (Thompson, 1967): In the case of *pooled interdependence*, units are connected loosely and each unit receives and contributes to the whole. An example of pooled interdependence is sharing of resources. In pooled interdependence demand for coordination is low. In *sequential interdependence*, output of one unit becomes input for the next. Demand for coordination is higher than in the case of pooled interdependence. Also, in *reciprocal interdependence*, output of one unit may become input for another unit. However, here the output of the second unit may become input again for the first unit.

While coordination in sequential interdependence can still be relatively well defined, coordination in reciprocal interdependence is continuous and it is not always possible to clearly specify it beforehand.

The level of planner-interdependence may serve as a proxy for the extent to which planners of the same or different companies exchange orders and resources. If planner-interdependence is low, planners work in an isolated fashion and exchange orders and resource only rarely. At high planner-interdependence on the other hand, planners frequently exchange information which facilitates a frequent exchange of orders and resources.

The impact of intensity of DSS use on planner-interdependence

Horizontal integration, such as information exchange between planners of the same or different companies, can be supported by information technology (Doll and Torkzadeh, 1998). DSS functionality can support interdependence between planners in various ways. Overviews and evaluation functionality make it easier for planners to find out which exchange of orders and resources is beneficial. Planners can make faster and better decisions whether to accept an offer from other planners. DSS can also support planners in examining which addition to or deletion in the order or resource set will increase planning satisfaction. The more often planners use DSS, the more detailed knowledge they have on the solution space. As a result they are better informed about which orders and resources may be candidates for exchange. Based on this knowledge of solution space they can more easily assess requests for exchange from planners. By using DSS more often, planners are faster at making these exchange decisions. In addition to decision speed, using a DSS more often will also increase perceived decision accuracy. Consider the case, when a planner receives a request for exchange for which it is difficult to decide if it really will improve performance. When a planner does not know solution space well, he might prefer not to engage in the exchange. However, the more accurate knowledge planners have gained from frequently using DSS, the more likely they will see even small benefits to performance. This leads us to the following Hypothesis:

H 2: Intensity of DSS use increases planner-interdependence.

The impact of planner-interdependence on planning satisfaction

From an abstract point of view, plans of a network can be guaranteed to be optimal only if they have been calculated in a centralized fashion. However, companies do not always want to engage in such network wide optimization due to technological and organizational difficulties related to data sharing. When centralized planning is not an option, frequent information exchange can serve as an alternative to align plans of single entities. With more frequent exchange of orders and resources, changes in customer demand and resource capacity can be ripple faster through the logistics chain. In that way higher planner-interdependence can lead to a better allocation of orders and resources. Therefore we formulate the following Hypothesis:

H 3: Planner-interdependence increases planning satisfaction.

4.3 Method

4.3.1 Measurement

We adapted scales from the literature in order to measure frequency of usage (Lerch and Harter, 2001; Ahmad and Schroeder, 2001), planner-interdependence (Morris and Steers, 1980; Price, 1997), and planning satisfaction (Sanders and Courtney, 1985; Lilien et al., 2004).

As the adoption of the measurement scale for intensity of DSS usage is relatively extensive we explain it in more detail. Ahmad and Schroeder (2001) measure the use of EDI by asking (1) if EDI was used or not and if yes, (2) what the extent of orders supported by EDI technology was. The advantage of this scale is that it controls for variance in absolute orders and measures only the amount of support. To illustrate, sending 20 out of 100 orders via EDI represents a different level of support (20%) than 20 out of 20 orders (100%). We used a perceptive version of this measurement as pretests showed that it is too difficult for respondents to answer precisely how often they used a certain technology for a certain decision. The decision we focus on is *order route assignment*. We distinguish eight different DSS functionalities which may be used for that decision: lists regarding routes, orders and drivers, functionality to compare alternatives regarding efficiency, punctuality, travel and rest times of drivers, as well as profit

Table 4.2: Measurement of intensity of DSS use

Intensity of DSS use, Ahmad and Schroeder, 2001; Lerch and Harter, 2001	
item	item description
If a planner assigns routes to orders he always makes use of ...	
AG1	... an electronic list (excel, transport management system, etc.) of routes
AG2	... an electronic list of orders
AG3	... an electronic list of drivers
	... a software tool that enables planners to make good comparisons regarding ...
AE1	... efficiency (e.g. empty distance)
AE2	... punctuality
AE3	... travel and rest times of drivers
AE4	... profit
AS1	... a software tool that chooses the optimal solution

AG refers to alternative generation, AE to alternative evaluation and AS to alternative selection
items were measured on a Likert scale with answer categories ranging from
(1) very much agree, to (7) very much disagree, and, in addition,
the answer category (8) we do not have this technology

and, finally, a software tool that chooses the optimal solution. The different functionalities support the decision making process to a varying extent and are related to the framework of Lerch and Harter (2001) as follows: Provision of lists mainly supports alternative generation, comparison facility supports also the step of alternative evaluation and the tool that chooses the optimal solution supports all three steps. The process that we employed for the scale of intensity of DSS use is also referred to as the facet design approach (Guttman, 1954; Hox, 1997). The measurement of intensity of DSS use for the eight different DSS functionalities is presented in Table 4.2.

4.3.2 Pretest

We used several forms of pretests to exploit their complimentary sets of benefits (Snijkers, 2002). We conducted interviews with seven colleagues that have extensive experience with survey methodology, working experience in the logistics sector, or as an organization and technology consultant. To improve the wording of the questions, we conducted four on-site in-depth interviews using cognitive interview techniques (Dillman, 2000). Answering survey questions triggers thought processes, and respondents are encouraged to report on that. These insights allow the researcher to examine whether the obtained answer reflects the information the researcher was looking for. In addition, we conducted a focus group pretest in which we went through the questionnaire together with three practitioners. The strong point of focus groups is to discover difficulties and mismatches related to exactness and clarity of the examined concepts. Focus groups tend to stimulate more engaging discussion than interview settings.

4.3.3 Data collection

We sampled our survey participants from the publicly available membership listing of Transport Logistiek Nederland, a trade organization for transport companies representing about 6000 Dutch transport companies (TLN, 2008) which is about half of the 12098 registered Dutch transport companies on the first of january 2008 (NIWO, 2008, p.20). Companies can be part of several so-called subgroups of this trade organization. We selected specific subgroups which we expected to have a high rate of technology adoption. The sea container subgroup just recently had developed a DSS for evaluating transport distances. For the physical distribution group, extensive use of technology is an entry requirement. Courier and express companies often have to work in congested time periods, which is a DSS adoption antecedent (Golob and Regan, 2003). Two subgroups were included because we expected them to have high adoption rates of real-time monitoring systems. Conditioned transport uses real-time monitoring systems to let customers monitor the temperature of their freight. Transport services for the construction sector need to monitor their trucks as the information when a truck will be available for another job only becomes available during or at the end of execution.

A team of students called the companies trying to reach the head of the planning department or the senior planner. If the respondent agreed to participate we asked for the email address. In some cases we could only reach a colleague or secretary. If this person would give us the email address of the head of the planning department or the senior planner we included it in our database. We sent an email to each respondent including a cover letter and a web link to the online questionnaire. Respondents did not have to fill in the complete survey in one session. By clicking on the link in the invitation email they could resume the session where they left it. About one quarter (24.29%) of participants made use of this option. We sent a first reminder after one week and two weeks later a second reminder. 607 companies agreed to participate, and 210 of them completed the questionnaire. From this set, we only used those 161 companies for further analysis, in which planners *assign orders to routes*, resulting in an effective response rate of 26.52%.

Table 4.3 presents an overview of our respondents. In 90.67% of the observations the respondent has a rank of senior planner or higher. 7.45% of the companies in our sample are one-man companies. This indicates that the respondents have a high level of knowledge both on the planning process and the performance of the planning department. Table 4.4 provides an overview on the company profiles. 14.29% of our sample companies have an annual sales volume of less than 100 Eur, and 17.39% have an annual sales volume of 5 000 000 Eur or more. 21.74% of our sample companies have 10 employees or less, and 14.91% have 100 or more employees. We also asked respondent to characterize the innovator type of the respective company. 13.66% of our sample companies are technological innovators, 45.34% are fast imitators and 40.91% are cost reducers. We conclude that we have a heterogenous sample.

Table 4.5 gives an overview of the planning criteria of the sample and their relative importance. The right column contains the number of respondents for whom the respective criterion is not applicable. Customer satisfaction (besides punctuality) is the most

Table 4.3: Respondent profile

Respondent rank	count (%)
Company owner	48 (29.81)
Managing director	8 (4.97)
Manager	28 (17.39)
Head planning department	28 (17.39)
Senior planner	22 (13.66)
Junior planner	4 (2.48)
One man company	12 (7.45)
no answer/other	11 (6.83)
total	161 (100)

Table 4.4: Company profile

Annual sales volume	count (%)
less than Eur 100	23 (14.29)
Eur 100 - Eur 499 999	17 (10.56)
Eur 500 000 - Eur 1 999 999	25 (15.53)
Eur 2 000 000 - Eur 4 999 999	23 (14.29)
Eur 5 000 000 and more	28 (17.39)
no response	45 (28.00)
Number of employees	count (%)
less than 10	35 (21.74)
10 - 19	36 (22.36)
20 - 49	28 (17.39)
50 - 99	22 (13.66)
100 and more	24 (14.91)
no response	16 (9.94)
Innovator type	count (%)
technological innovator	22 (13.66)
fast imitator	73 (45.34)
cost reducer	66 (40.99)

Table 4.5: Planning criteria

Criterium	mean (std. dev.)	not applicable (% of sample)
Customer satisfaction (beside punctuality)	4.31(1.15)	1 (0.62)
Punctuality	4.15 (1.18)	1 (0.62)
Profit of trip	4.03 (1.29)	4 (2.48)
Capacity utilization	3.66 (1.27)	7 (4.35)
Number used trucks	3.36 (1.32)	14 (8.70)
Empty distance	3.20 (1.37)	12 (7.45)

scale from 1 important to 5 extremely important, 6 not applicable

important planning criteria. Criteria related to efficiency such as capacity utilization and number of trucks are named less often than profit and punctuality. Respondents also mentioned other criteria important for their planning: good balance of work over the whole fleet, availability of personnel, and adherence to regulations regarding driver hours.

Table 4.6 gives an overview of why respondents invest in technology. The most important reason is to have a better communication between planners, drivers and clients. The second important reason is to improve the overview of the planning. Criteria related to planning performance such as faster planning, higher capacity utilization rate, less empty distance, higher reliability are all important to more than one third of the sample. Best practice in other companies is an investment reason for only 10 respondents (5.43% of the sample). Other reasons mentioned by respondents refer to faster and easier processing of administrative tasks, making planners conscious of costs, providing insight for clients, improving ability to deal with problems.

Table 4.7 gives an overview of the education of planners in our sample companies. In 29.19% of sample companies, planners have a level of education which at the most prepares them for vocational school. In 43.38% of sample companies, planners went to vocational school. In roughly one fourth of the sample companies, planners at least have a level of education that prepares them for advanced technical colleges or universities. In more than half of the sample companies, planners received no additional education (57.76%). In those companies in which planners received, the education was provided by vocational school (16.15%), within the company (14.19%) or both (6.21%).

Table 4.8 presents descriptive statistics on the planning process of our sample. For each characteristic the means and standard deviation are noted. For some character-

Table 4.6: Reasons to invest in technology

Reason	amount agree (% of sample)
better communication between planners, drivers and clients	102 (63.35)
better overview over planning (e.g. automatic reports)	89 (55.28)
higher capacity utilization rate	78 (48.45)
faster planning	74 (45.96)
less empty distance	67 (41.61)
more reliable working hour registration of drivers	67 (41.61)
more reliable planning	65 (40.37)
less planning mistakes	53 (32.92)
wish of client	44 (27.33)
more feasible planning	42 (26.09)
more trucks per planner	23 (14.29)
freight security	13 (8.07)
depend less on experience of planners	25 (15.53)
was a success for other companies (best practices)	10 (6.21)

Table 4.7: Education of planners

Level	count (% of sample)
Education level of planners comparable to ...	
... preparation level for vocational school or less	47 (29.19)
... vocational school	70 (43.48)
... at least preparation level for advanced technical colleges or university	41 (25.47)
no answer	3 (1.86)
Additional education	
yes, within the company	24 (14.91)
yes, vocational training	26 (16.15)
yes, both	10 (6.21)
no,	93 (57.76)
no answer	8 (4.97)

Table 4.8: The planning process

process characteristic	mean (std. dev.)	quantiles				
		0	25	50	75	100
		(min.)		median		(max.)
percentage of orders for which						
planners participate in price negotiation	45.09 (38.65)	0	10	35	85	100
amount shipments per planner	80.49 (143.75)	0	25	45	100	1200
amount drivers per planner per day	17.58 (15.20)	1	9	15	20	117
amount addresses per planner per day	59.14 (90.49)	0	15	40	70	800
amount route plans per planner per day	33.49 (35.65)	0	12	20	45	300
orders received on day of execution						
... before 10 o'clock	24.26 (20.27)	0	10	20	30	80
... after 10 o'clock	23.93 (25.30)	0	5	10	40	100
percentage of route						
plans changed during the day	20.24 (20.17)	0	5	10	30	100
average distance						
between pickup and delivery in km	219.54 (300.06)	0	40	100	300	2000
power units per company	27.16 (32.55)	0	7	15	37	200
percentage international trips	40.56 (36.26)	0	7.5	25	80	100
percentage temperature controlled trips	35.76 (41.20)	0	0	10	80	100

some of the companies did not provide some of the information, for all of the items n $\geqslant$ 149 istics variance is rather large and therefore we also included quantiles which give the reader a more detailed insight how values of a particular process characteristic are distributed. The minimum and maximum value for each process characteristic are given by the 0% and 100% quantile. The values for the quantiles are computed as follows. First all observations are ranked in ascending order by their value for the specific characteristic. Examining the value of the observation at the respective quantile gives the value represented in Table 4.8. For example, the 25% lowest ranked observations have a value for the given characteristic that is noted in the the 25% column. The following numbers give an insight into the planning process of our sample companies. Planners are involved in price negotiation for an average of 45% of all orders they deal with. On average, planner have to manage about 80 shipments, 17 drivers, 60 addresses and 33 tours in one day. For comparison, 75-80 is the amount of cities for which modern computers can be guaranteed to find the optimal solution for the traveling salesman problem within reasonable time (Toth and Vigo, 2002). The following numbers provide an intuition to what extent planners may be disturbed in their decision making processes. Planners receive 24% of all orders on the same day of execution before 10 o'clock and about the same amount after 10 o'clock (23.93%). On average, 20% of route plans are changed. The following numbers characterize the companies and their offered services. Sample companies have on average 27 power units, about 40% of trips are international and 35% are temperature controlled. Average distance between pickup and delivery is about 220 km (136.7 miles).

It is customary to assume that late respondents represent non-respondents. We tested for non-response bias by comparing early and late respondents (Malhotra et al., 2001; Chen and Paulraj, 2004). We received about 40% of responses after the first reminder message which was sent one week after the first email and classified them as late respondents. The t-test results show no significant differences between early and late respondents for the number of planners, planner-interdependence, innovator type, sales volume, full time employees, respondent type and most DSS functionalities. However, late respondents use electronic lists both of orders (AG2) and drivers (AG3) more often than early respondents. Non-response bias poses a threat to external validity. For establishing external validity it is preferable to have samples that are representative of the population. However, studies based on a sample that is not representative are not uncommon. For example, Nahm et al. (2003) encountered under- and overrepresentation of firm types in their study.

Table 4.9: Assessment of measurement quality for planner-interdependence

Item	Item description	ITC[a]
Planner-interdependence, Cronbach α = 0.81; Morris and Steers, 1980; Price, 1997		
I1	In order to do his job well, a planner needs to be able to get along well with other planners	0.63
I2	The planning job requires that planners work closely together with other planners	0.60
I3	Planners often take over orders from other planners	0.59
I4	A planner can do his job only well, if other planners do that also	0.57
I5	Planning is always being discussed in detail with other planners	0.56
I6	Planners often take over drivers/routes from other planners	0.48

[a] ITC indicates item to total correlation

Table 4.10: Assessment of measurement quality for planning satisfaction

Item	Item description	ITC[a]
Planning satisfaction, Cronbach α = 0.86; Sanders and Courtney, 1985; Lilien et al., 2004		
P1	Route planning of the planning department is of high quality	0.79
P2	I am satisfied with the decisions of the planning department	0.71
P3	The route plans of the planning department are very efficient	0.71
P4	The planning department makes transport related decisions fast	0.69
P5	The performance of the planning department contributes greatly to profit	0.52

[a] ITC refers to item total correlation

As size can influence organizational structure (Blau, 1970), possibly influencing planner interdependence, we also controlled for size by measuring the number of planners in a company. In principle, the size of a transport company can also be measured by owned and hired trucks, but this seems a less stable measure than number of planners. We calculate scores for planner-interdependence and planning satisfaction by taking the average over the items. Table 4.10 presents the assessment of measurement quality for planner-interdependence, and Table 4.9 for planning satisfaction. Both Cronbach α are above 0.80 which is a very good reliability level (DeVellis, 2003).

4.4 Discussion of results

It was not compulsory to answer all of the DSS usage items due to a programming error. As a result, there are three kinds of responses for each DSS functionality. Respondents either (1) indicated their intensity of using the DSS functionality, or (2) they indicated that they do not have such a DSS available or (3) they did not give a response. For the analysis regarding DSS functionality, we used only the first group.

4.4.1 Impact of intensity of DSS use on planning satisfaction

Our first hypothesis states a positive impact of intensity of DSS usage on planning satisfaction. We tested the first hypothesis with the following Equation:

$$\textit{planning satisfaction} = \beta_0 + \beta_{\textit{intensity of DSS use}} + \beta_{\textit{size}} + e; \tag{4.1}$$

Table 4.11 shows the regression results for our first Hypothesis. Only intense use of DSS functionality that compares alternatives regarding efficiency (AE 1) has a significant effect on planning satisfaction at the liberal 10% level. As a result, Hypothesis 1 is supported. However, this support is rather weak.

4.4.2 Impact of intensity of DSS use on planner-interdependence

The second Hypothesis states that intensity of DSS use increases planner-interdependence. We used the following Equation to test the second Hypothesis:

$$\textit{planning-interdependence} = \beta_0 + \beta_{\textit{intensity of DSS use}} + \beta_{\textit{size}} + e; \tag{4.2}$$

The regression results are presented in Table 4.12. The intensity of DSS use for comparing alternatives regarding efficiency (AE1) has a significant effect at the .01% level. The effect of this functionality on planner-interdependence is significant at a more conservative level than the effect of the same functionality on planning satisfaction. In addition, intense usage of DSS for comparing alternatives regarding travel and rest times of planners (AE3) and profits of trips (AE5) increases planner-interdependence.

Table 4.11: Impact of intensity of DSS use on planning satisfaction

DSS functionality	β_{DSSuse}	β_{size}	R^2 (%)	Adj. R^2 (%)	n
If a planners assigns routes to orders he always makes use of ...					
... an electronic list (excel, transport management system, etc.) ...					
AG1 ... of routes	0.0250	-0.0244	1.03	-0.52	131
AG2 ... of orders	0.0276	-0.0283	1.44	-0.23	121
AG3 ... of drivers	0.0463	-0.0308	2.77	0.97	111
... a software tool that enables planners to make good comparisons regarding ...					
AE1 ... efficiency (e.g. empty distance)	0.0804*	-0.0505**	6.71	4.90	106
AE2 ... punctuality	0.0620	-0.0423*	4.74	2.89	106
AE3 ... travel and rest times of drivers	0.0660	-0.0398*	4.51	2.64	105
AE4 ... profit	0.0594	-0.0268	3.15	1.34	110
... a software tool ...					
AS1 ... that chooses the optimal solution	0.0166	-0.0294	1.73	-0.36	97

* denotes a $p < .1$; ** denotes a $p < .05$; *** denotes a $p < .01$ and **** denotes a $p < .0001$;
DSSuse denotes intensity of DSS use for the respective functionality
model specified in Equation 4.1

Also, intense usage of DSS functionality providing an electronic list of orders increases planner-interdependence. The results support Hypothesis 2.

Hypothesis 3 states that planner-interdependence increases planning satisfaction. To test this we used the following Equation:

$$\textit{planning satisfaction} = \beta_0 + \beta_{\textit{planner-interdependence}} + \beta_{\textit{size}} + e; \qquad (4.3)$$

Table 4.13 represents the regression results for Hypothesis 3. Planner-interdependence has a significant impact on planning satisfaction supporting Hypothesis 3.

Table 4.12: Impact of intensity of DSS use on planner-interdependence

DSS functionality	β_{DSSuse}	β_{size}	R^2 (%)	Adj. R^2 (%)	n
If a planners assigns routes to orders he always makes use of ...					
... an electronic list (excel, transport management system, etc.) ...					
AG1 ... of routes	0.0603	0.0288	2.9	1.38	131
AG2 ... of orders	0.0859*	0.0241	4.39	2.77	121
AG3 ... of drivers	0.0088	0.0438	2.00	0.19	111
... a software tool that enables planners to make good comparisons regarding ...					
AE1 ... efficiency (e.g. empty distance)	0.1608***	0.0307	10.72	8.98	106
AE2 ... punctuality	0.0762	0.0405	4.19	2.33	106
AE3 ... travel and rest times of drivers	0.1054*	0.0491	6.31	4.47	105
AE4 ... profit	0.1340***	0.0337	7.85	6.12	110
... a software tool ...					
AS1 ... that chooses the optimal solution	-0.0276	0.0548*	3.85	1.80	97

* denotes a $p < .1$; ** denotes a $p < .05$; *** denotes a $p < .01$ and **** denotes a $p < .0001$;
DSSuse denotes intensity of DSS use for the respective functionality
model specified in Equation 4.2

4.4.3 Mediating impact of planner-interdependence

The DSS functionality to compare alternatives regarding efficiency (AE1) increases both planner-interdependence and planning satisfaction. This suggests that planner interdependence can mediate the impact of AE1 on planning satisfaction. In order to test this effect, we adopted the approach of Baron and Kenny (1986) using the following equation:

$$\begin{aligned} \textit{planning satisfaction} = \; & \beta_0 + \beta_{\textit{intensity of DSS usage}} + \beta_{\textit{size}} \\ & + \beta_{\textit{planner-interdependence}} + e; \end{aligned} \tag{4.4}$$

Table 4.14 presents the regression results for Equation 4.4 for all eight DSS functionalities. DSS functionality AE1 is the only one for which there is a direct effect of intense DSS use on planning satisfaction, and therefore the only candidate functionality

Table 4.13: Impact of planner-interdependence on planning satisfaction

Independent variable	$\beta_{pl-idep}$	β_{size}	R^2	Adj. R^2	n
planner-interdependence	0.29227***	-0.16196**	9.83	8.69	161

* denotes a $p < .1$; ** denotes a $p < .05$; *** denotes a $p < .01$ and **** denotes a $p < .0001$;

model specified in Equation 4.3

pl-idep denotes planner-interdependence

for a mediating effect. The DSS functionality AE1 does not have a significant impact on planning satisfaction when controlling for planner-interdependence. This suggests that the performance impact of intense usage of DSS functionality to compare alternatives regarding efficiency (AE1) is fully mediated by planner-interdependence. In other words, the data suggests that intense use of DSS functionality only increases planning satisfaction if it first increases planner-interdependence.

4.5 Conclusions

Based on data from 161 transport companies, we compared two usages of DSS: (1) use for isolated optimization versus (2) use for collaborative optimization. We collected data on intensity of usage for eight DSS functionalities which we define based on the framework of Lerch and Harter (2001). If using a DSS increases planning satisfaction, then by use of collaborative optimization and not by use of isolated optimization. As a result we conclude that use of collaborative optimization is more important than use of isolated optimization.

We are surprised by the extent to which *use of collaborative optimization* dominates the *use of isolated optimization*. There may be different reasons for this. Planners may simply not be concerned with spending considerable effort on isolated optimization. They may be ignorant of the complexity of OR problems and of the potential savings related to using OR tools and techniques. Low adoption rates provide evidence for low expectations practitioners may have from OR-based DSS. Another reason may be that planners use DSS largely not for generating plans but for event handling. For example 15% of participants in the aforementioned California based survey have fixed schedules which

Table 4.14: Mediating impact of planner-interdependence

DSS functionality	β_{DSSuse}	β_{size}	$\beta_{pl-idep}$	R^2% (Adj. R^2%)	n
If a planners assigns routes to orders he always makes use of ...					
... an electronic list (excel, transport management system, etc.) ...					
AG1 ... of routes	0.0288	- 0.1278	0.2947***	9.46 (7.32)	131
AG2 ... of orders	0.0265	-0.1488	0.2787***	8.87 (6.53)	121
AG3 ... of drivers	0.1213	-0.1849**	0.3281***	13.32(10.88)	111
... a software tool that enables planners to make good comparisons regarding ...					
AE1 ... efficiency (e.g. empty distance)	0.0742	-0.2472***	0.3880****	20.15 (17.80)	106
AE2 ... punctuality	0.0937	-0.2189**	0.3674***	17.67(15.52)	106
AE3 ... travel and rest times of drivers	0.0720	-0.2260**	0.4036****	19.77(17.39)	105
AE4 ... profit	0.0555	-0.1492	0.3358 ***	13.53(11.09)	110
... a software tool ...					
AS1 ... that chooses the optimal solution	0.0603	-0.1972**	0.3554***	13.87(11.09)	97

* denotes a $p < .1$; ** denotes a $p < .05$; *** denotes a $p < .01$ and **** denotes a $p < .0001$;
model specified in Equation 4.4
DSSuse denotes intense use of DSS for the respective functionality
pl-idep denotes planner-interdependence

may have been set up by the manager possibly with the use of OR algorithms (Golob and Regan, 2003). The planners in our sample companies may be responsible only for event handling, which they do both by using DSS and by asking their colleagues for help.

Another reason for the dominance of use of collaborative over use of isolated optimization may be related to measurement error. Respondents may be especially impressed by the benefit of DSS for collaborative optimization and as a result underestimate the impact of the use for isolated optimization. This skewed impression might be responsible for the results we obtained. However, the conclusion remains valid that practitioners appreciate decision support especially designed for collaborative optimization.

What are the implications of our results for OR algorithms? Traditionally, the interaction between OR algorithms and planners is that planners can run OR algorithms with varying input data (Anthonisse et al., 1988). Calculating solutions such as the optimal order-resource assignment seems to be aiming at the use of isolated optimization. For supporting use of collaborative optimization, OR algorithms may provide slightly different answers such as: which additional order or resource would increase overall performance? Or, subcontracting which order or resource to which conditions will contribute to overall performance? By providing these answers, processing skills of computers are exploited and at the same time the human planners can keep a "feel for the data". Looking for a feasible solution is often an easier problem than examining which additions or subtractions from problem instance will improve solution quality as the latter potentially includes examining a much larger set of solution spaces.

DSS may also offer negotiation agents in order to support use for collaborative optimization. Agents are small software modules that take more information into account than the human decision maker, and can adapt more quickly to changes in the environment such as customer demand or fluctuation in resource availability (Banker and Kauffman, 2004). Such functionality can save planners the possibly time consuming activities of searching for orders and resources themselves. In order to discuss change in plans on the phone it is important that DSS provide results quickly. Then it might be useful to sacrifice solution quality in order to have the necessary speed of decision support. Such systems are sometimes also referred to as real-time as opposed to batch-oriented systems which might take over night to finish their processing (Zani, 1970).

Further research may investigate further uses of DSS. While this does not exactly answer the question of Bendoly et al. (2006), why OR-based DSS are used in practice to a low extent, such research can give indications what can be done in order to introduce more OR techniques to the decision making process. More uses of DSS may be explored by conducting field studies. Researchers can observe the questions planners ask their colleagues or which answers they look for while using DSS or while communicating with clients. These observations may produce further usages of DSS that can open up novel ways of introducing OR to the planning process. New usages may also be found by examining literature. We agree with Devaraj and Kohli (2003) that business-process-orientation, a concept closely linked to planner-interdependence, provides an excellent starting point for examining additional usages of technologies. Another area may be information systems literature, which contends that users not necessarily use DSS to increase their objective solution quality (Todd and Bensabat, 1999). Further research in the use of DSS can therefore draw on and contribute to both Operations Management and Information Systems literature. Hopp (2004) underlines that multidisciplinary research may contribute to advancing the field of management science further.

While this chapter provides new insights into the use of DSS, the results and recommendations should be taken with care. The data only address a very specific assignment problem. As a result it is difficult to generalize the findings to other decisions. Also, the low R^2 indicate that there are more factors affecting planning satisfaction. We also collected data on intensity of DSS usage for the route driver assignment, but there was even less impact on planning satisfaction. Further, we used planner-interdependence as a proxy for exchange of orders and resources. The item of the planner-interdependence construct most closely related to exchange of orders and resources (item I6 "Planners often take over drivers/routes from other planners") has the lowest item to total correlation. As a result the planner-interdependence construct might not be a very close proxy to exchange of orders and resources. However, it does capture not only frequency of exchange but also whether planner helped each other in difficult situations. Further research might profit from using objective measurement and distinguishing aspects such as frequency and motivation for exchange. Transport is a commodity which facilitates the exchange of orders and resources. Further research needs to be carried out to investigate the use of DSS of collaborative optimization in other contexts, such as for example inventory related decision making in a supply chain.

Chapter 5

Increasing the performance impact of monitoring technology by organizational structure

5.1 Introduction

Sophisticated monitoring technologies offer many possibilities for transport companies. The more timely and more accurate data lay the foundation for faster decision making at a higher solution quality (McFarlane and Sheffi, 2003). In addition, planners need to spend less time on check up calls, and they are able to manage more trucks (Deierlein, 1996). Further, planners are in a better position to anticipate problems and solve them before they occur. On the other hand, clients of transport companies which adopted sophisticated monitoring systems are more likely to place orders shortly before or even during execution (Rishel et al., 2003). Already now, 40% of transport orders are not executed according to their initial plans (Calisti et al., 2005). Apparently, sophisticated monitoring technology changes not only the characteristics of the input data for decision making but also the context in which these decisions are carried out. As a result of adopting sophisticated monitoring tools, the decisions that determine actual performance are possibly made under increasing time pressure and with more frequent client interruptions (Frei, 2006). In order to enjoy the benefits of sophisticated monitoring technologies without the costs related to decision making under chaotic circumstances, transport companies need to know how to make "intelligent use" of sophisticated monitoring systems (Lee and Özer, 2007).

From other technologies we know that not the investment, but the way technologies are used, determines their impact on performance (Goodhue and Thompson, 1995; Devaraj and Kohli, 2003; Devaraj et al., 2007). Among the first to use sophisticated monitoring technologies are planners. Their role is even more important than in the "traditional" setting, as OR-based DSS perform poorly in environments with frequently changing customer demand, or customer demand that becomes known only very close to execution (Powell et al., 2000; Giaglis et al., 2004). Humans do have diagnosis skills superior to those of OR-based DSS, simply because it is often not profitable and sometimes not possible to communicate all possible exceptions to the computer (Blattberg and Hoch, 1990). Therefore, in a real-time context, planners are to an increasing extent the ones which decide whether to allow a client to place or change orders late and how to incorporate this changes into the existing plans. In addition, planners need to find a good balance for dividing their time and attention to monitoring and control activities (Lerch and Harter, 2001). If human planners play a more important role as decisions in transport environments are increasingly taken close or even during execution, then one way to use sophisticated monitoring technology intelligently, is to support planners in doing so.

We examine the extent to which organizational structure can support planners in capitalizing on sophisticated monitoring technology. We model this with the following research question: what is the impact of planning effort on planning satisfaction and to what extent is this moderated by organizational structure? Based on Organizational Information Processing Theory (OIPT) we expect that organic as opposed to mechanistic organizational structures will be more beneficial as planners spend more effort on their task (Galbraith, 1973; Galbraith, 1974; Tushman and Nadler, 1978).

5.2 Framework and hypotheses development

5.2.1 Conceptual model

The conceptual model is schematically represented in Figure 5.1. It assumes that sophisticated monitoring technologies can increase planning effort. We do not formally test this relation as we think that the intelligent use of sophisticated monitoring technolo-

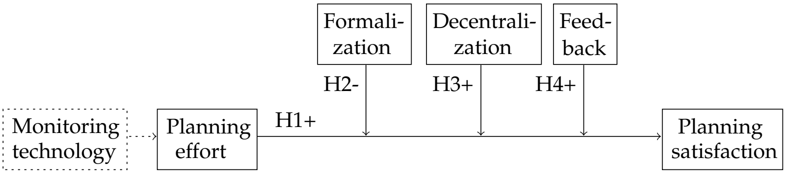


Figure 5.1: Organizational structure in planning departments

gies, reflected by an increase in planning effort, is not automatic but depends on the experience, skill level, and volition of the individual planner. Hypothesis 1 describes the impact of planning effort on planning satisfaction. The relationship between planning effort and planning satisfaction is hypothesized to be moderated by organizational structure. We measure three dimensions of organizational structure directly mentioned in OIPT (Galbraith, 1973; 1974): formalization, decentralization and feedback. These three dimensions are also referred to as management enablers.

5.2.2 Impact of planning effort on planning satisfaction

Planning satisfaction

We use planning satisfaction as a dependent variable. Remember that planning satisfaction is defined as the satisfaction with the decisions of the planning department. The definition and measurement is based on the work of Sanders and Courtney (1985) and Lilien et al. (2004) which refer to the construct as decision satisfaction. This definition of performance not only addresses the objective solution quality of plans (e.g. how close is the resulting plan to the optimal solution) but also decision speed. The definition of planning satisfaction and the other constructs used in this chapter are summarized in Table 5.1.

Planning effort

Our definition of planning effort is based on routinization which is the "degree to which jobs in an organization are repetitive" (Perrow, 1967; Price and Mueller, 1986) and problem solving demand which "reflects the more active, cognitive processing required to

Table 5.1: Definition of constructs

Construct	Definition	References
Independent variable		
Planning effort	Complexity of the search process and cognitive processing carried out by planners as they perform the planning task, prevent or recover errors.	Perrow, 1967; Van de Ven and Delbecq, 1974; Jackson et al., 1993; Wall et al., 1995; Goodhue, 1995; Price, 1997
Moderating variables: Organizational structure		
Formalization	The extent and level of specification of formal procedures and rules given by management to planners to prescribe how they have to behave in given situations.	Galbraith, 1974; Malhotra et al., 2001; Wang, 2001
Decentralization	The extent to which planners can take planning decisions including handling of exceptions without management guidance and can influence decisions regarding personnel and planning equipment.	Galbraith, 1974; Hage, 1980; Malhotra et al., 2001
Feedback	The extent to which planners are informed about individual or general performance of the company.	Galbraith, 1974; Rungusanatham, 2001; Melnyk et al., 2004
Dependent variable		
Planning satisfaction	Satisfaction with decisions of the planning department.	Sanders and Courtney, 1985; Lilien et al., 2004

prevent or recover errors" (Jackson et al., 1993; Wall et al., 1995). We refrain from using the label task difficulty since planners may be confronted with similar tasks but do not necessarily solve them in similar ways. The level of difficulty in planning depends to some extent on the one executing it. For example, given small problem instances, planners can solve the traveling salesman problem comparatively well to models and heuristics (Hill, 1982; Applegate et al., 2007). In a controlled setting as the laboratory it might be easy to assess which approach is actually better, however, in practice it is quite difficult to assess the quality of planning actions (Gary et al., 1995). Planning effort also reflects the extent to which planners engage in certain activities. For instance, a planner might realize that there is only a partially filled up truck and then proceeds to search for additional orders by asking colleagues, clients or examining electronic transportation markets. Other planners might not have this knowledge and therefore do not spend the necessary effort. They might see there is a problem, but they cannot do anything about it. Planners may also differ in the extent that they are able to detect problems before they arise and as a result they spend varying effort on related planning activities.

Impact of planning effort on planning satisfaction

Highly dynamic environments require a high level of planning effort. Planners can spend effort in solving problems before they arise and they can handle events as they become aware of them. When planners can meet this demand and deliver high quality plans even if uncertainty is high, they will contribute to planning performance. Planning effort does not only contribute to high planning performance when dealing with unexpected problems but also when dealing with unexpected opportunities. For example, planners can increase efficiency by filling up empty distance or less-than-full truck loads. If planners are able to assess and exploit such short term business opportunities they also contribute to planning performance. This leads us to our first Hypothesis:

Hypothesis 1: Planning effort increases planning satisfaction.

5.2.3 Moderating impact of management enablers

Organizational Information Processing Theory (OIPT)

Organizational structure addresses the allocation of responsibilities and tasks (Nahm et al., 2003). Organizational structure creates a context for carrying out the planning task and as such it impacts the process and outcome of planning. Mechanistic versus organic structures are two extremes of a continuum scale of possible structures for organizational units (Lawrence and Lorsch, 1967; Nahm et al., 2003).

OIPT describes how uncertainty and organizational structure relate to each other (Galbraith, 1973; 1974). The unit of analysis in OIPT is an organizational unit, such as a company, business unit, or department. The factor that drives the best choice of organizational structure for a given unit is uncertainty. The problem with uncertainty is that it diminishes the ability to prepare for decision making (Galbraith, 1974). Technology, demand, and supply are general sources of uncertainty for companies (Chen and Paulraj, 2004). Uncertainty for departmental units can, in addition, stem from complexity and interdependence of tasks, the environment of the department as well as interdependence with other units (Tushman and Nadler, 1978). As the organizational structure moves from mechanistic to organic, planning departments improve their ability to deal with uncertainty (Lawrence and Lorsch, 1967; Galbraith, 1974; Nahm et al., 2003). If future events occur as expected, mechanistic organizations can handle the same problem with less resources than organic ones, resulting in higher efficiency. Preparation for routines is emphasized less in organic organizations. Organic structures differ from mechanistic ones in that employees are given the authority and resources for solving problems instead of executing prescribed ways of handling them. If unexpected events occur, employees can use their knowledge and experience to assess a situation and find an adequate solution fast. As a result, they handle unexpected, difficult events better than employees in mechanistic organizations which work according to the rules and guidelines of their manager.

Formalization

Formalization refers to the extent to which there are rules and guidelines describing how tasks should be carried out and the strictness of enforcing these rules (Malhotra et al., 2001; Wang, 2001). In an environment with low formalization there are few such rules and not adhering to them does not result in severe punishment. In a planning department with high formalization, rules and guidelines can include aspects such as which software or heuristics to use for planning, how drivers and clients should be dealt with, what to do in case of traffic jams or machine breakdowns but also how to negotiate on prices or carry out administrative tasks. Stable environments with high certainty allow managers to predict actions that are necessary to reach a given aim (Galbraith, 1974). This increases efficiency as workers do not have to plan appropriate actions themselves. Guidelines prevent planners from having to reinvent the wheel. With increasing uncertainty of the environment, managers are less able to predict future events and establish most beneficial reactions beforehand. By their very nature, planning departments have to deal with a certain level of uncertainty. If planners handle arising problems in real-time, the uncertainty planners are dealing with increases. Then adequacy and efficacy of formalization as a management enabler decreases. The more cognitively demanding information processing of planners is, the more difficult it becomes for managers to predict and provide the adequate rules and guidelines for the respective decision making processes. This leads us to the following Hypothesis:

Hypothesis 2: Formalization weakens the impact of planning effort on planning satisfaction.

Decentralization

Decentralization describes the extent to which authority is given to lower ranks in an organizational unit (Hage, 1980; Malhotra et al., 2001; Wang, 2001). If decisions are made only by the head of the planning department, the level of decentralization is low. In planning departments with a high level of decentralization, the opinion and preferences of planners are taken into account when hiring new personnel, investing into planning technology or other changes affecting the way of working. Planners in decentralized departments can determine the sequence of tasks themselves and do not need to go through a lengthy authorization process when exchanging orders or resources with other companies. Decentralization allows organizational units to become more flexible and better deal with unexpected events (Galbraith, 1974). If planners can influence the way they carry out their jobs, their experience with transport but also knowledge on their own way of working determine how to proceed in situations that require creative problem solving. Problematic cases tend to occur in an irregular fashion. Planners which can schedule their activities without management interference can adapt better to these irregular occurrences. Therefore, we state the following Hypothesis:

Hypothesis 3: Decentralization strengthens the impact of planning effort on planning satisfaction.

Feedback

Feedback refers to the information given regarding past behavior (Te'eni, 1991; Ahmad and Schroeder, 2001). The impact of feedback on the performance of individuals or organizational units is best captured in the adage that "what you measure is what you get" (Kaplan and Norton, 1992, p. 71). Three purposes of performance measuring can be distinguished (Melnyk et al., 2004): control, communication and improvement. In planning departments with low levels of feedback, planners are left in the dark how they performed in the past. In a situation with high level of feedback, planners receive information about performance indicators such as on-time delivery, empty distance drive, gasoline and labor costs. The rationale behind feedback is that it allows to steer performance without having to specify how this should be achieved. This will be especially valuable in highly uncertain environments where expert knowledge is needed and decision making situations are difficulty to predict (Galbraith, 1974). Management informs planners of the goals they want to achieve and leaves it to the planners on how to achieve them (Galbraith, 1974). With increasing planning effort, the complexity of the planning task increases and feedback informs planners which goals to focus on, thereby facilitating the decision making process. As a result, we state the following Hypothesis:

Hypothesis 4: Feedback strengthens the impact of planning effort on planning satisfaction.

5.3 Method

The constructs are measured based on scales found in the literature (Hage, 1980; Sanders and Courtney, 1985; Price and Mueller, 1986; Wall et al., 1995; Ahmad and Schroeder, 2001; Malhotra et al., 2001; Lilien et al., 2004). For a description of the pretest and the data collection process we refer to chapter four as the data for this chapter were collected in the same survey.

From the 210 responses that we obtained, we excluded four observations, since planners in the respective companies do not carry out either order-route or route-driver assignments. Further, we excluded responses from 22 one-man companies as they are manager and planner in one, and the concept of organizational structure does not apply. The 184 observations that are included in this analysis constitute an effective response rate of 30.61%.

It is customary to assume that late respondents represent non-respondents (Lambert and Harrington, 1990; Chen and Paulraj, 2004). We tested for non-response bias by comparing early and late respondents (Malhotra et al., 2001; Chen and Paulraj, 2004). Responses within the first week are classified as early respondents (about 40%), the rest as late respondents. The t-tests did not result in significant difference between late and early respondents regarding planning effort, feedback, decentralization, formalization, planning satisfaction, amount of planners, innovator type, sales, full time employees and respondent type. Consequently, non-respondent bias does not seem to be a problem.

Like in chapter four, we control for size, measured by the amount of planners, as it might influence organizational structure (Blau, 1970). As in chapter four, we calculate the values for the variables by averaging all items of the respective variable after the assessment of measurement quality.

Assessment of measurement quality process

The measurement quality analysis regarding planning effort is presented in Table 5.2. Planning effort has a Cronbach α of .83, which constitutes a very good reliability level (DeVellis, 2003). All items have an item to total correlation higher than the acceptance level of .3 (Nunally and Bernstein, 1994).

Table 5.3 presents the assessment of measurement quality of the organizational structure, also referred to as management enablers. The Cronbach α's are .79 or higher, which is a respectable reliability level (DeVellis, 2003). The exploratory factor analysis using Varimax method (orthogonal rotation) resulted in clean loadings on three factors. Using the significance level of 40 (Malhotra et al., 2001), no item loads significantly on more than one factor. However, two items have a loading factor less than 40 and are excluded from further analysis (item O6 ”There are significant penalties for planners violating procedures” and item O20 ”Planners always get compliments when they do their work well”). All items have an inter-item correlation above the acceptable level of .3 (Nunally and Bernstein, 1994).

Table 5.2: Assessment of measurement quality: planning effort

Item	Item description	ITC[a]
Planning effort, Cronbach α = 0.83; Price and Mueller, 1986; Wall et al., 1995		
T1	In order to prevent problems in their work, planners need very good knowledge of the transport process	0.72
T2	Planners have to be very creative in their work	0.70
T3	In order to prevent problems in their work, planners need very good knowledge of laws and regulations	0.62
T4	Planners spend a lot of time thinking	0.57
T5	Planners encounter often problems, for which the solution is not directly obvious	0.55
T6	Every day planners learn something new	0.46

[a] Item to total correlations

5.4 Discussion of results

5.4.1 Impact of planning effort on planning satisfaction

Hypothesis 1 states that planning effort increases planning satisfaction. We test this Hypothesis with the following Equation:

$$\textit{planning satisfaction} = \beta_0 + \beta_{\textit{planning effort}} + \beta_{\textit{size}} + e; \tag{5.1}$$

The results for the regression of planning effort are reported in Table 5.4. Planning effort has a positive impact on planning satisfaction at the .01% significance level. This supports Hypothesis 1.

5.4.2 Moderating effect of management enablers

Hypothesis 2, 3 and 4 state that the management enablers moderate the impact of planning effort on planning satisfaction. In order to investigate the moderating effect of management enablers we specified two different models -one without (Equation 5.2) and one with the interaction term (Equation 5.3)- for each management enabler.

$$\begin{aligned}\textit{planning satisfaction} = \; & B_0 + B_{\textit{planning effort}} + \\ & B_{\textit{management enabler}} + B_{\textit{size}} + e;\end{aligned} \tag{5.2}$$

Table 5.3: Assessment of measurement quality: management enablers

Item	Item description	ITC [a]	Loading factor 1	Loading factor 2	Loading factor 3
Formalization, Cronbach α = 0.81 (0.81)[b]; Malhotra et al., 2001					
	The job description of planners is...				
O1	... complete	0.67	95	18	1
O2	... up-to-date	0.66	94	12	1
O3	If there is a problem in planning we have a procedure to deal with it	0.59	45	-9	19
O4	Planing rules and procedures are explicitly documented	0.58	43	-13	14
O5	Comprehensive rules exist for all routine activities (duties and responsibilities)	0.50	40	4	16
O6	There are significant penalties for planners violating procedures	0.44[c]	35	03	17
Decentralization, Cronbach α = 0.79; Malhotra et al., 2001; Hage, 1980					
	Planners are closely involved in all decisions related to...				
O7	... new technologies for their job	0.57	9	70	24
O8	... new personnel for the planning department	0.54	-5	67	-1
O9	... organizational changes that have consequences for their way of working	0.52	8	67	12
O10	... new drivers	0.47	6	52	3
O11	Planners hire trucks from other transport companies autonomously	0.55	-6	52	7
O12	Planners work autonomously when they solve problems	0.51	-2	51	15
O13	Planners search contact autonomously with other transport companies in order to improve planning (e.g. avoid empty km)	0.47	1	43	26
Feedback, Cronbach α = 0.87 (0.86)[b]; Ahmad and Schroeder, 2001					
	Planners receive detailed feedback on their performance regarding ...				
O14	... punctuality	0.71	16	10	82
O15	... driving and resting time of drivers	0.70	16	18	80
O16	... profitability of trips	0.63	6	27	72
O17	... empty distance	0.70	17	12	68
O18	... gasoline usage	0.61	16	3	64
O19	Planners receive daily feedback on the quality of their work	0.63	21	20	51
O20	Planners always get compliments when they do their work well	0.39[c]	17	25	27

[a] Item to total correlations

[b] Cronbach α in parenthesis is before dropping items

[c] indicates dropped items

Table 5.4: Regression analysis: impact of planning effort on planning satisfaction

Independent variable	Regression coefficients			
	β_1	β_2	$R^2(\%)$	$Adj.R^2(\%)$
planning effort	0.5121 ****	-0.0286	26.47	25.66

* denotes a $p < .1$; ** denotes a $p < .05$; *** denotes a $p < .01$ and **** denotes a $p < .0001$; model specified in Equation 5.1

Table 5.5: Regression analysis: moderating effect of organizational structure

without interaction term						
management enabler	B_{pe}	B_{me}		B_{size}	$R^2(\%)$	$Adj.R^2(\%)$
formalization	.51367****	.0327		-.0093	26.62	25.40
decentralization	.3780 ****	.3486****		.0088	38.27	37.25
feedback	.4901 ****	.1048 **		-.0054	28.38	27.19
with interaction term						
management enabler	B_{pe}	B_{me}	B_{pe*me}	B_{size}	$R^2(\%)$	$Adj.R^2(\%)$
formalization	.034	-.6081 **	.1135 **	-.0144	28.88	27.29
decentralization	1.0311****	1.1324 ***	-.1408***	.0059	40.89	39.57
feedback	1.0338****	.9195 ***	-.1412**	-.0063	31.15	29.61

* denotes a $p < .1$; ** denotes a $p < .05$; *** denotes a $p < .01$ and **** denotes a $p < .0001$; model specified in Equations 5.2 and 5.3

pe denotes planning effort, *me* stands for management enabler

Table 5.6: Correlation matrix

construct	mean	S.D.[a]	1	2	3	4	5	6
planning effort	5.66	0.88	1.00					
formalization	3.95	1.04	-0.08	1.0				
decentralization	5.07	0.94	.36 ****	.08	1.0			
feedback	4.06	1.17	.15 **	.29****	.33 ****	1.0		
planning satisfaction	5.72	0.87	.51 ****	0.0 *	.51 ****	.21***	1.0	
size	2.88	2.74	-.06	.02	-.17**	-.10	.-0.06	1.0

* denotes a $p < .1$; ** denotes a $p < .05$; *** denotes a $p < .01$ and **** denotes a $p < .0001$;

[a] S. D. refers to standard deviation

$$\begin{aligned} \textit{planning satisfaction} = \quad & B_0 + B_{\textit{planning effort}} + B_{\textit{management enabler}} + \\ & B_{\textit{management enabler * planning effort}} + B_{\textit{size}} + e; \end{aligned} \tag{5.3}$$

The results of Equation 5.2 and Equation 5.3 for each management enabler are presented in Table 5.5. All three interaction terms are significant, indicating the existence of a moderating effect (Baron and Kenny, 1986). Because of problems related to measurement error, Carte and Russel (2003) suggest to examine the ΔR^2, that is, the impact of the interaction term on variance explained. In all three cases the variance explained increases by about 2%, which is comparable to the study of Malhotra et al. (2001) which examine the moderating effect of organizational structure for increasing impact of CAD technology.

Hypothesis 2 states that formalization will weaken the impact of planning effort on planning satisfaction. The nature of the moderation effect, and in particular if it is weakening, is examined with the approach proposed by Aiken and West (1991). Figure 5.2 shows the interaction pattern for formalization. Two lines are computed based on unstandardized co-efficients and the value of one standard deviation above and the value for one standard deviation below the mean as well as for the effect of low and high formalization respectively as suggested by Cohen and Cohen (1983). At the level of high planning effort there is no difference between the impact of low and high formalization. At the level of low planning effort, formalization decreases performance. The interaction pattern shows that increasing formalization does not have a weakening moderating

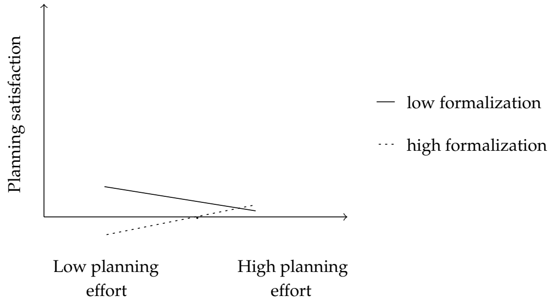


Figure 5.2: Interaction pattern of planning effort and formalization

effect. Rather, the moderation is such that formalization is detrimental to performance at low planning effort. With increasing planning effort formalization stays detrimental but decreases in extent. At high planning effort, formalization has no effect on planning satisfaction. Therefore, Hypothesis 2 is not supported.

Hypotheses 3 and 4 state that decentralization and feedback strengthen the effect of planning effort on planning satisfaction. The moderating effect of decentralization and feedback was analyzed in the same way as for formalization. The interaction plot for decentralization is shown in Figure 5.3 and the interaction plot for feedback is shown in Figure 5.4. Like formalization, there is no effect of neither decentralization nor feedback on planning satisfaction in case of high planning effort. Therefore, Hypotheses 3 and 4 are not supported. Instead, the data suggests that both decentralization and feedback have positive effects only in planning departments with low planning effort. To summarize, while we expected the moderating effect of management enablers to increase with increasing planning effort, the data indicate the opposite. Management enablers have no effect in planning departments with high planning effort. However, in environments with low planning effort we do see the predicted pattern for uncertain environments (Lawrence and Lorsch, 1967; Galbraith, 1973): when formalization is detrimental, decentralization and feedback are beneficial.

The correlation matrix presented in Table 5.6 shows that planning effort is correlated with decentralization and feedback. This is an undesirable solution as it makes the interpretation of the results more difficult (Baron and Kenny, 1986). But the correlation between decentralization and planning effort can be explained in the following

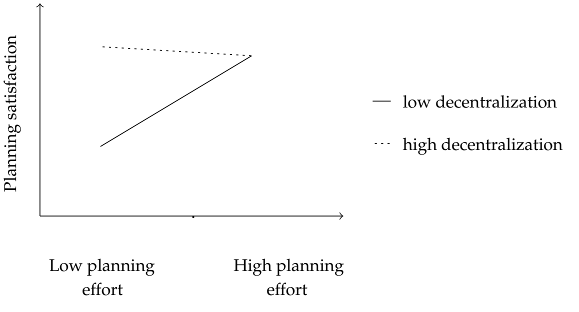


Figure 5.3: Interaction pattern of planning effort and decentralization

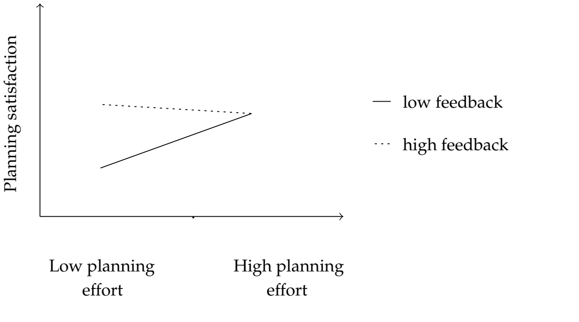


Figure 5.4: Interaction pattern of planning effort and feedback

way. For example, it is possible that planners in departments with high decentralization choose software and create an environment that will allow them to focus on the difficult problems. In such a condition, "additional" decentralization seems to have no further effect. However, in planning departments with low decentralization, planners might use software that is not conducive to concentrating on difficult problems. Any additional decentralization or freedom on how to solve problems will result in a performance increase. This is an example of the complex ways in which organizational structure and technology can interact. It relates to the emergent perspective, which is one of the different structures of causality employed by researchers studying organizational structure and technology (Markus and Robey, 1988). As feedback and decentralization are related (view Table 5.6), the correlation between feedback and planning effort might work in a similar way.

Our results initially seem to be in contrast with literature, which states that formalization is beneficial in environments with low uncertainty, and detrimental in environments with high uncertainty (Lawrence and Lorsch, 1967; Galbraith, 1974; Nahm et al., 2003). We argue that our results extend literature by suggesting boundaries in which organizational structure can moderate performance of planning effort as presented in Table 5.7. In certain environments, formalization is beneficial. However, for such environments it might not be necessary to have planning departments. Planning departments become necessary with an increased level of uncertainty which will also highten the level of planning effort required from planners. Our results suggest that at that stage, planners invest so much effort that they cannot be reached anymore by the respective organizational structure. This argumentation might also explain why there is little moderating impact of organizational structure on the performance effect of CAD technology (Malhotra et al., 2001).

We test this argumentation by running the regressions for the moderating effect (Equations 5.2 and 5.3) separately at high and low uncertainty. The following pattern will support our argumentation. Under low uncertainty all three interaction effects are significant with the following direction: positive for formalization and negative for decentralization as well as feedback. Under high uncertainty significant interaction terms for all three management enablers are not significant. We distinguish between high and low uncertainty by median-split. The results are reported in Table 5.8. Five of the six interaction terms are in line with the pattern that supports our argumentation. Only the interaction between formalization and planning effort under low uncertainty is not

Table 5.7: Suggested impact boundaries for the moderating effect of organizational structure

Uncertainty	very low	low	high
Planning effort	very low	low	high
Necessity to have a planning department	very low	low	high
Impact of management enablers			
Formalization	beneficial	detrimental	no impact
Decentralization	detrimental	beneficial	no impact
Feedback	detrimental	beneficial	no impact

significant whereas we expected it to be significant with a negative sign. We conclude that our argumentation based on uncertainty can be an explanation for the deviation from our Hypotheses.

In addition to uncertainty, we tested if other variables, namely level of education and characteristics of the planning process, can explain the deviation from our Hypotheses. In Table 5.9 we report on the interaction effects from the regression results (based on Equation 5.3) for each management enabler both above and below the median for a given variable. The first line in Table 5.9 indicates the pattern which supports our argumentation. Only one of these - amount of addresses per planner per day - has a match with the pattern equal to or higher than that of uncertainty. Some other characteristics roughly related to complexity have four out of six possible matches with the indicated pattern. These are: amount shipments per planner, amount drivers per planner per day, percentage of route plans changed during the day, power units per company, percentage international trips and percentage temperature controlled trips. In addition, special additional education has four out of six possible matches.

5.5 Conclusions

Based on data from 184 transport companies, we find that planning effort increases planning satisfaction. In environments with low planning effort, an organic organizational structure can strengthen the impact of planning effort on planning satisfaction. With increasing planning effort, the moderating impact of organizational structure de-

Table 5.8: Regression analysis: moderating effect of organizational structure - under low and high uncertainty

			high uncertainty			
without interaction term						
management enabler	B_{pe}	B_{me}		B_{size}	R^2(%)	Adj.R^2(%)
formalization	0.3435***	0.1613*		-0.1224	15.81	13.38
decentralization	0.2480***	0.3515 ****		-0.0633	24.56	22.38
feedback	0.3252***	0.0879		-0.1025	14.00	11.52
with interaction term						
management enabler	B_{pe}	B_{me}	B_{pe*me}	B_{size}	R^2(%)	Adj.R^2(%)
formalization	0.5084	0.5569	-0.4194	-0.1237	16.01	12.75
decentralization	0.0188	-0.0126	0.4788	-0.0672	24.71	21.79
feedback	0.7649**	1.1810	-1.2218	-0.0852	15.31	12.02
			low uncertainty			
without interaction term						
management enabler	B_{pe}	B_{me}		B_{size}	R^2(%)	Adj.R^2(%)
formalization	0.5533****	-0.1253		0.0439	35.15	32.45
decentralization	0.3924 ****	0.4291 ****		0.1351	48.10	45.93
feedback	0.55334 ****	0.1911**		0.0733	37.21	34.59
with interaction term						
management enabler	B_{pe}	B_{me}	B_{pe*me}	B_{size}	R^2(%)	Adj.R^2(%)
formalization	-0.0354	-0.8134**	0.8383	0.0159	38.55	35.09
decentralization	1.4400 ***	1.4366 ****	-1.7548***	0.10020	54.10	51.51
feedback	1.0717***	1.0036 **	-1.0274*	0.0533	39.72	36.32

* denotes a $p < .1$; ** denotes a $p < .05$; *** denotes a $p < .01$ and **** denotes a $p < .0001$;
model specified in Equation 5.3, *pe* stands for planning effort, *me* stands for management enabler

Table 5.9: Interaction terms at low and high levels of uncertainty, education levels of planners and various process characteristics

	interaction terms at median and below			interaction terms above median		
	form.	dec.	feed.	form.	dec.	feed.
expected pattern	+	-	-	not sign.	not sign.	not sign.
uncertainty	0.8383	-1.7548***	-1.0274*	-0.4194	0.4788	-1.2218
education level of planners [a]	1.6480	-0.5348	0.1565	-0.7743	-0.7633	-2.6965*
additional education[b]	0.8198**	-1.0976**	-0.8342	1.7051**	-0.9936	-0.6044
process characteristics:						
percentage of orders for which						
planners participate in price negotiation	0.8723	1.5800	-0.5535	0.8975*	-2.0206***	-1.5758***
amount shipments per planner	0.9799*	-1.1114*	-0.9382	1.1696*	-1.1265	-1.4242
amount drivers per planner per day	0.9153**	-1.0752*	-0.9286	0.4334	-1.2021	-2.9505***
amount addresses per planner per day	0.8358*	-1.4220***	-1.1720**	0.8756	-0.5457	-1.2176
amount route plans per planner per day	1.3084***	-1.044*	-0.9087	-1.9723**	-0.6967	-1.6820*
order received on day of execution ...						
... before 10 o'clock	0.4861	-0.5314	-0.8110	0.1843	-0.9380	-0.9328
... after 10 o'clock	-1.005	-2.0558**	-2.0646**	1.2906***	-1.0199*	-0.9918
perc. of route plans changed during the day	0.7069	-0.9769*	-0.7061	0.7478	-1.1068	-1.4552
average distance between pickup and delivery	-0.1513	-1.3661*	-1.3449	1.2392***	-1.5522***	-1.3154**
power units per company	0.6941	-0.7528	-0.9434*	0.5280	-1.0643	-0.9632
percentage international trips	1.0075**	-1.1336 *	-0.5809	-0.3931	-0.3874	-1.9538*
percentage temperature controlled trips	0.4563	-1.3402**	-1.2457**	1.7051**	-0.9936	-0.6044

* denotes a $p < .1$; ** denotes a $p < .05$; *** denotes a $p < .01$; and **** denotes a $p < .0001$;

interaction term $B_{managementenabler*planningeffort}$ from model specified in Equation 5.3

[a] instead of using the median we divided the sample in education level up to or higher than vocational school

[b] instead of using the median we divided the sample in presence or absence of additional education

creases.

We argue that the moderating effect of organizational structure on the impact of planning effort on planning satisfaction decreases because of uncertainty. However, some other factors namely education and process characteristics related to complexity may provide further reasons for the deviation from our hypotheses that our data suggests. Our results may serve as a starting point for further research to explain why the impact of management enablers not only changes direction, but also their extent.

When planning effort is low, organic organizational structures outperform mechanistic ones. However, our data suggests a limitation to the effectiveness of management enablers. As planning effort increases, the impact of organizational structure decreases. Planning departments with low problems solving effort will profit from more organic organizational structure, that is low formalization, high decentralization and high level of feedback. For planning departments with high level of planning effort, these management enablers do not serve to neither increase nor decrease the effect of planning effort on planning performance. Given that organic forms do not harm planning performance, managers are on the safe side if they have more organic structure in the planning department.

We argue that sophisticated monitoring technologies will increase planning effort for planners. This claim is based on earlier studies and anecdotal evidence (Lerch and Harter, 2001; Rishel et al., 2003). We also collected data on adoption of monitoring technology but the results were inconclusive. The inconclusive results can be an indication that planners and their managers lack the knowledge on how to make the most out of monitoring technology (Lerch and Harter, 2001; Lee and Özer, 2007). We also collected and analyzed data on *perceived usefulness of communication systems with drivers* which may be interpreted as a proxy for intelligent use of sophisticated monitoring technologies. The results regarding perceived usefulness of communication systems with drivers correspond to the results regarding planning effort. Formalization has detrimental effect on planning performance if perceived usefulness of communication systems with drivers is low, and both decentralization and feedback have positive effects. In planning departments with a high level of perceived usefulness of communication systems with drivers management enablers have no effect. Since perceived usefulness of communication systems with drivers has similar results as planning effort, we conclude that impact of intelligent use of sophisticated monitoring technologies on planning performance is moderated by organizational structure as the results reported on for planning effort.

We argue that our results contribute towards the question: What is the right organizational structure as planners make more intelligent use of sophisticated monitoring technologies? However, we cannot draw conclusions the question on how to make intelligent use of sophisticated monitoring technologies. In order to do so, the construct of media richness might be a useful starting point. Media richness refers to the capability of a communication channel to transfer rich information, that is, modify comprehension in a specified length of time (Daft and Lengel, 1984; Daft and Lengel, 1986). Depending on the context, different media are more useful than others. E.g. sophisticated monitoring technologies are more useful for checking up execution status than are telephone conversations. On the other hand, more personal communication modes provide better support for collaborative problem solving. Therefore, we conclude that an intelligent use of sophisticated monitoring technologies is only an addition to existing monitoring processes. In particular, we expect that telephone to remain an important communication channel to support collaborative problem solving with drivers.

The results of this study should be interpreted with care. The analyses are based on a single method approach eliciting data from single informants. As a result, we cannot exclude informant bias or systematic error caused by the method (common method variance). Further we used a perceptive measurement of planning performance which may not be as accurate as objective measures, such as efficiency, service and speed. Planning effort is correlated with the moderating variables decentralization and feedback. Taking the emergent perspective of the framework of Markus and Robey (1988) organizational structure and technology are closely intertwined and cause and effect cannot always be separated neatly. Therefore, the correlation between dimensions of organizational structure and technology-related independent variables can not always be eliminated in a field study.

Chapter 6

Conclusions and further research

6.1 Summary of main findings

Planning technology does not automatically improve planning performance. Low adoption rates of specialized OR-based DSS indicate that we not only need to know which advice to give to planners, but also how to give it (Golob and Regan, 2003; Bendoly et al., 2006; Loch and Wu, 2007; Dietrich, 2007). This places the decision making process of the planner at the center of attention for improving performance in planning departments. The human factor plays an even more important role in real-time transport environments, in which planners might additionally be confronted with frequently disturbing clients, possible information overload and time pressure. In order to generate theory that may contribute to creating higher synergy between planner and planning software, this thesis studies four mechanisms of fit between the planning task and planning technology in a real-time transport context.

Chapter 2 focuses on the match between presentation of a DSS and the task as it is presented in the head of the user. The argumentation is based on cognitive fit theory and a heuristic which can produce a systematic bias for decision making under uncertainty (Tversky and Kahneman, 1973; Vessey, 1991; Vessey and Galletta, 1991; Shaft and Vessey, 2006) The chapter examines the effect of agent-based and OR-based DSS presentation on perceived usefulness and to what extent this impact differs for decision makers with low or high-analytical cognitive style and for decision makers under low or high time pressure. In the experiment, low-analytics and decision makers under time pressure find the agent-based DSS more useful than the OR-based DSS. The analysis showed that cognitive fit can better predict variance in perceived usefulness between both approaches than other indicators, such as ease of understanding and trust. This opens up new ways to increase adoption of DSS in practice. The academic contribution is to apply cognitive fit theory to a presentation of problem solving approaches and extend it by including the moderating impact of cognitive style and time pressure.

Chapter 3 examines the impact of presentation structure on the sequence of decisions that planners take in order-resource assignments. Data presentation structure can influence the sequence in which planners process orders, but not the sequence in which they process resources. In addition, alert messages can influence in which subjects process orders. As time pressure increases the impact of these warning signals on decision sequence increases for low-analytics but not for high-analytics. This suggests that alert messages, for instance issued by monitoring agents, play an important role in steering but also possibly disturbing cognitive processes of planners, which has implications for the design of monitoring agents. The academic contribution is to establish the notion of order-orientation and resource-orientation for presentation structures and examine how planners deviate from rational decision making when they do not use OR-based DSS for order-resource assignment (Larkin and Simon, 1987; Jarvenpaa, 1989).

Chapter 4 compares two uses of DSS: A direct effect of intense DSS use on planning satisfaction which we label use of isolated optimization and an indirect effect, labeled use of collaborative optimization, consisting of two parts: the effect of intense DSS use on planner-interdependence and the effect of planner-interdependence on planning satisfaction. The data collected from 161 Dutch transport companies indicates that the second use is more important. Whenever the intensity of DSS use increases planning satisfaction, it does so by first increasing planner-interdependence. This has implications for the design of DSS. They should provide support for planners in their negotiations with other planners. Furthermore, the results suggest that automatic negotiation as for example enabled by agent technology can improve planning. The academic contribution is to add further evidence that technology sometimes has indirect effects on performance and that these can be more important than the direct effects (Devaraj and Kohli, 2003; Devaraj et al., 2007). The contribution to Behavioral Operations Management is to examine one such effect in a typical Operations Management setting.

Chapter 5 examines the effect of planning effort on planning satisfaction and to what extent this effect is moderated by organizational structure. The argumentation is based on Organizational Information Processing Theory (Galbraith, 1973; Galbraith, 1974). The three examined dimensions of organizational structure are: formalization, decentralization and feedback. The data collected from 184 Dutch transport companies suggest that the predictions of Organizational Information Processing Theory hold when planners exert little effort: formalization has a negative moderating effect, while decentralization and feedback have a positive moderating effect. With increasing planning effort the extent of the moderating effects diminishes. The managerial implications inform which changes in organizational structures are most likely to yield performance increases. The academic contribution is twofold. First, the study applies and tests Galbraiths theory to planning departments. Second, the findings can explain mixed results in literature, which sometimes reports on moderating effect of organizational structure on performance impact of technology and sometimes does not (Malhotra et al., 2001).

6.2 Managerial implications

Transport companies are faced with a shift of which planning actions determine planning performance. There is a general trend towards shorter lead-times and, in addition, sophisticated monitoring technologies have given this trend an extra momentum. Management of transport companies needs to ensure higher information processing capabilities in their planning departments. However, DSS which can provide computation capacity with higher solution quality at a higher speed in comparison to human handling are adopted only to a small extent. Apparently, practitioners do not recognize the potential of theses systems or they do not know how to create synergy effects between planners and planning software. The four mechanisms of task-technology fit examined in this dissertation provide pointers as to how to leverage on planning technology. For instance, managers might examine to what extent presentation of tools matches the task as perceived by planners. When planners do not deliberatively initiate DSS, the presentation structure of data may influence the sequence in which they process the orders. Especially salient features such as alert messages can have an effect of the sequence of processed orders. The sequence of processed orders can by itself have an effect on the decision quality. Finally, planning performance in transport benefits greatly from collaboration between planners. Consequently, planning software should provide overviews that facilitate finding good candidates for such an exchange or quickly assessing proposed exchanges from other planners. Management can also influence the effect of planning effort of individual planners on planning satisfaction by means of the orga-

Table 6.1: Questions to examine task-technology fit in a real-time transport context

Question	Respective chapter
Are the terminology and problem solving mechanism of the planning software immediately intuitive? If not, is it possible to adjust text messages, labels and icons to match the respective planning context?	Chapter 2
Does the decision support system provide functionality to ”sort by optimality”? Does the information system issue salient information items such as alert messages that can disturb planners?	Chapter 3
Does the software generate an overview of orders that a planner should try to subcontract? Is this overview so quick and easy to use and navigate that planners can use it during a telephone conversation? Does the planning software support or carry out participation in online auctions for transport services?	Chapter 4
Is it possible to have less rules, or a more lenient enforcement of them? Can management include planners more in decisions regarding new personnel, software and other aspects regarding the planning process? Can management provide more feedback to planners?	Chapter 5

nizational structure. However, it should be noted that this moderating impact becomes smaller as planning effort increases. Basically, more organic organizational structures provide a positive moderating effect. In concrete, organic organizational structures entail less rules, or a more lenient enforcement of them, more authority for planners and more feedback. For a summary on questions, that managers can use to examine task-technology fit view Table 6.1.

6.3 Limitations

We have pointed out the detailed limitations for each study in the respective chapter. Here, we just provide a summary. The first two mechanisms were tested with data collected from a lab experiment. The data was collected in a controlled setting which may have little resemblance with the respective real-life situation posing a threat to external validity. As a result, the effects that we have found might exist in real-life but be too small to actually make a difference. In addition to the task that was executed, also the subjects executing the task differ between the laboratory setting and practice. While students can be "surrogates for managers" (Remus, 1986) we do think that the generalizability of our results may be limited and further research needs to be conducted to corroborate external validity of our findings. However, given the low adoption rates, the results even at this stage of external validity may provide valuable insights for increasing the extent to which the benefits of OR are introduced to the planning processes in practice.

Limitation of the data collected from the survey is that we only elicited data from one source per company (single informant approach). Possibly our data contains informant bias and systematic error caused by the way of data collection. Further we use mainly perceptive measures which may be subject to further systematic errors. In addition, the analyses showed that our data include a non-response bias which limits the generalizability of our findings.

6.4 Contribution and further research

This dissertation contributes to the largely uncharted territory of Behavioral Operations Management in three ways. By adopting the task-technology fit theory (Goodhue and Thompson, 1995), this thesis introduces a new perspective on the planning task: planning is software use. Viewing planning as software use provides a theoretical lense complementary to abstract problem formulations often encountered in logistics literature. As a result we may more easily think of factors that are not part of, for example, well-defined variations of the planning task, but that do influence decision outcomes. This relates to the second scientific contribution of this dissertation, which is to investigate mechanisms that may enhance notoriously low adoption rates of OR algorithms (Bendoly et al., 2006; Loch and Wu, 2007; Dietrich, 2007). To this effect we studied the role of presentation for both manual order-resource assignment as well as deliberative initiating of OR-based DSS. Further, we examined the role of the DSS as a whole in practice and described implications for the functionality that may increase DSS adoption. The third contribution is to more closely examine the role of various human factors in the planning process, such as cognitive style, collaborative problem solving skills between planners of the same or of different companies as well as planning effort and organizational structure.

We contend that task-technology fit will play a more important role as the extent of real-time services in transport increases. Then the shortcomings of both planner and planning technology for solving the planning task alone will become more pronounced. The propensity of human planners for rational and thorough decision making declines with time pressure (Maule and Svenson, 1993). OR-based DSS assume problem formulation that can never entirely describe real-life situations, and this deviation will only increase with the frequent changes in demand typical for real-time transport (Anthonisse et al., 1988; Powell et al., 2000; Giaglis et al., 2004). On the other hand, DSS can easily provide the calculation skills that human planners lack, and human planners often have tacit knowledge on demand that will be useful for OR-based DSS. Further research may study ways on how to better leverage the complementing skill sets of planners and planning technology.

Further research may study which information planners need in order to carry out their diagnosis tasks and if these vary as a function of the individual and the respective task. Computers can support planners in searching orders and resources that may be candidates for exchange. Further research can examine how and when these candidates should be presented to the planner to maximize objective solution quality and minimize disturbances to cognitive processes. Such studies may be especially beneficial if they are carried out in a real-life setting with a case study or field experiment approach. But also quantitative studies may contribute to a better synergy between planner and planning software. Humans have better diagnosis skills than computers and can inform the computer e.g. on reliability of data. The straightforward application is that the computer requires the user to give a demand distribution for every event or information item relevant to the task. However, this is time consuming and cumbersome for users and therefore promises little success in terms of adoption. But planners may be willing to share some of the information they have on demand variability. This can be exploited in the following way. The OR algorithm may examine solution space and based on that make a judgement for which information items it is important to know the distribution and ask the planner on demand distribution only for a small selection of information items.

In order to be relevant to practice, studies on real-time planning may need to include additional dependent variables. Efficiency and service of the executed plan will continue to be important measures. However, in order to reach that, researchers may need to consider measures such as decision speed and the flexibility of a plan to incorporate future changes in demand (Gary et al., 1995). A small change in input may cause an OR-based DSS to give a solution that is very different from the previous one. This is possible from a mathematical point of view, but undesirable from a Behavioral standpoint. First it might give the impression that the OR-based DSS is too sensitive and therefore not appropriate for a constantly changing environment. Second, the planner is the one which needs to spend the effort in communicating the change to drivers, clients and possibly fellow planners. If using the DSS goes along with this increase in effort, adoption rates may suffer.

Exploiting real-time information is difficult due to the possible information overload and the need to decide when to focus on monitoring and when on control activities (Lerch and Harter, 2001). Lerch and Harter (2001) compare supporting real-time monitoring and control with teaching how to add large numbers. Typically students are taught that to write one number in the first line, then the second number in the second line and use the third line for writing down the solution. The solution is reached by a set of steps each containing smaller additions which the human mind can handle. In order to secure the correct solution, these steps need to be carried out in a certain order. Further research may study what are the steps necessary for decision making in a real-time environment, and the framework by Lerch and Harter (2001) may provide a starting point. In addition, further research may study the amount of information that humans can handle when carrying out logistics decisions. Quantitative studies can contribute by finding the right sequence to these steps. Empirical studies based on information systems may explore how the information should be placed on screen to optimally support information processing.

The new possibilities to support, manipulate and disturb cognitive process of decision makers require more in-depth studies of human-computer-interaction in planning (Lurie and Mason, 2007). Further, it is important to apply and test human-computer-interaction in the targeted context. The knowledge gained from emergency situations (e.g. fire alarm) is only partly applicable to planning. Consider for example alert messages which can inform users of changes in the execution status by means such as pop-up windows, blinking text fields and sounds. Which option is the best? As this thesis has shown, alert messages which can be issued by monitoring agents can influence the decision making process of planners. Disturbing a planner might only be beneficial to overall performance in some cases, e.g., for very profitable clients. Further research can examine different levels of interruption, and their performance impact in a lab experiment. Also data collected from planners in field studies can give insights into how to notify planners of changes in customer demand or execution status that are perceived as useful as opposed to disturbing. In addition, further research can examine interaction of human assistants and human decision makers. What are the characteristics of interaction between a decision maker and a good assistant both before and during provision of decision support? By providing answer to these questions further research can contribute to theories of task-technology fit for decision making in real-time planning and thereby higher levels of synergy between planner and planning technology.

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Appendix A: Handbook for experiment participants

LovingLogistics

Introduction

LovingLogistics is a transport company headquartered in Rotterdam, the Netherlands. It was established in 1978 and its business is to pick up full containers from one place (*pickup location*) and to transport them to another (*delivery location*). Clients specify the earliest point in time when containers can be picked up (*pickup time*) and the latest point in time they should be delivered (*preferred delivery time*). The LovingLogistics company has a total of 3 trucks to do this task and a truck can only carry one order at a time. The LovingLogistics company aims to have high customer service (delivery before or at the preferred delivery time) and efficiency (little empty km - distance that trucks are moving without transporting something). If a truck is just standing still the whole day, it will not generate empty km and therefore not affect efficiency in this game. Late minutes and empty km are the only important performance indicators for the LovingLogistics company.

For every completed order you receive 3000 points, for every empty km -1 point and for every late minute -50 points.

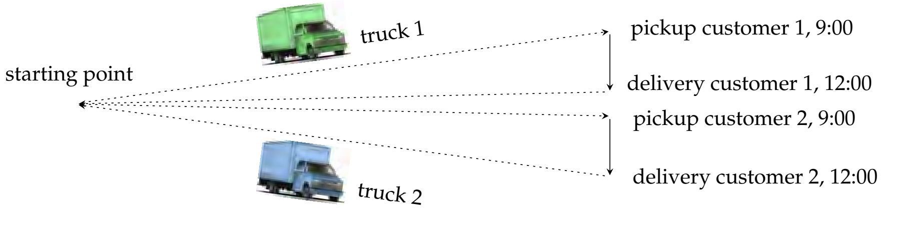
The problem

You are the planner at the LovingLogistics company. Your task is to decide which truck is executing which order and communicate these plans to the truck drivers. The goal is to have a high degree of service (deliver before or at the specified *preferred delivery time*) and of efficiency (*low amount of empty km*) as possible.

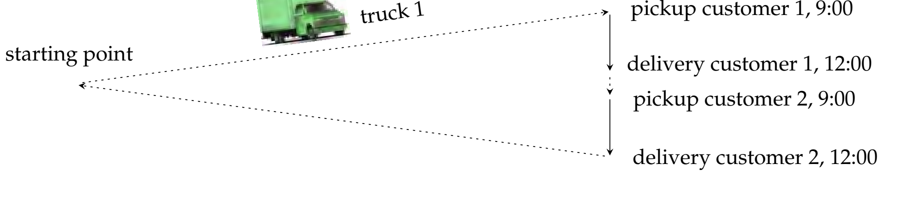
As often in life, one decision has several implications and reaching one goal somehow excludes another, you are faced with a typical trade-off. Sometimes the planner in the LovingLogistics company has to make a trade-off between efficiency and service.

Consider the example below, where the LovingLogistics company has to deliver orders for two customers: In the first case the efficiency is relatively low, since the total distance driven by trucks is longer (dashed line shows empty km). However, if both clients want their goods to be picked up and delivered at the same time, this is the only way to have a high service level. In case 2 only one truck is used, efficiency is higher, service levels are also high. The first case could have been done with one truck like case 2, then the order of customer 2 would have been picked up and delivered late, which is bad customer service.

Case 1: relatively low efficiency, relatively high service



Case 2: relatively high efficiency, relatively low service



Your task: During the lab experiment you will plan for eight days under different conditions. For all conditions your task is to match orders and trucks. We are interested in how you evaluate the different interfaces that you will use and how this changes given that you have time pressure or that you do not have time pressure. Therefore we will ask you a set of questions after each planning day.

Next step now is to watch the introduction movie to see how the software works. You can find a description of the four interfaces (including how the decision support systems work) and frequently asked questions in the next pages of this handbook.

Process of the whole experiment session

- Introduction movie on the LovingLogistics software
- Warm up (to get used to system - no score keeping)
- Questions after warm-up

- 1st interface without time pressure (= start and stop time button available)
- Your opinion
- 2nd interface without time pressure (=start and stop time button available)
- Your opinion

- 1st interface with time pressure (= start and stop time button not available)
- Your opinion
- 2nd interface with time pressure (= start and stop time button not available)
- Your opinion

- 1st interface with DSS, without time pressure (=start and stop time button available)
- Your opinion
- 2nd interface with DSS, without time pressure (=start and stop time button available)
- Your opinion

- 1st interface with DSS, with time pressure (=start and stop time button not available)
- Your opinion
- 2nd interface with DSS, with time pressure (=start and stop time button not available)
- Your opinion

- Final questions
- Paper based test with figures (2 * 10 min)

We will do the paper based test together. If you are done before that you can read what you brought with you. Success!

Description of interfaces

Interface without DSS: fixed orders
Whenever a new order arrives in the incoming orders table, a new row will be added to the plan board. The orderIDs in the plan board are fixed, which means you cannot change the order-ID (like in the warmup), you can only change the truck.

Interface without DSS: fixed trucks
In this view the plan board has a separate part for each truck. You can assign orders by using the orderID - selection box for the respective truck. Once you have clicked the "tell driver" button, a new row will appear for that truck and you can plan another truck-order combination.

Decision support system (DSS): agent negotiation
When the "assign trucks" button is pressed the following happens: for every order and truck there is a software module (agent) taking care of it. These agents do what clients and truck drivers would do if they were to decide which truck driver should do which order: they negotiate. In addition, there is a managing agent, which is coordinating the negotiation. First every order agent negotiates with each truck agent to determine the performance. As a result every order agent has a ranking of which truck it would prefer. Then the managing agent asks each order about its best order-truck combination. The managing agent selects the best order-truck combination of all orders. The managing agent will repeat the process of selecting the best order-truck combinations until all orders have been assigned a truck.
This algorithm will find a good solution in most situations but not always the best.

Decision support system (DSS): column generation
When the "assign trucks" button is pressed the following happens: The system calculates the solution with an algorithm based on column generation. This is a mathematical procedure which uses the method of column generation and linear programming. It works like this: If you want to have the best solution you have to generate all possible solutions, calculate how good they are and then select the best. Since there are so many possible solutions, it is not possible to evaluate all. Column generation generates

a set of solutions and evaluates them by looking at only a specific aspect (=columns), and then selects the best. The trick is to choose a "good" set of columns for evaluation. The algorithm selected for LovingLogistics evaluates only those subsets that contain the order-truck combination with the highest total scores.
This algorithm will find a good solution in most situations but not always the best.

Frequently asked questions

What is the meaning of the triangle and the box in the virtual map?

The triangle represents the pickup location of an order (in this example order 241). The time given next to the orderID 241 tells you the pickup time of this order.
The box represents the order to be transported.

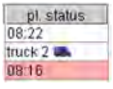
What is the meaning of the circle in the virtual map?

The circle represents the delivery location of the order. The respective orderID is written above the circle. The time in grey tells you the preferred delivery time (09:00 in the example).
Why are the colored delivery times sometimes the same for some trucks? The delivery times in green, blue and red tell you when the respective truck would arrive if you were to tell the driver to execute the order now.
In two situations these calculated delivery times can be the same: (1) the trucks have the same distance to the pickup point and as a result would pickup and deliver at the same time. (2) the trucks can have different distances to the pickup point, but they would all have to wait before being able to pickup. As a result they pickup and deliver at the same time.

What does highlight mean?

Highlight is part of the incoming orders table. If you click on a cell in the ”highlight” column the respective order will be marked in the virtual map; it will be black instead of grey. It will stay highlighted until you request another highlight by pressing on another cell in the highlight column or by pressing the ”e” or ”s” button.

What is the meaning of the pl. status?



Pl. status (short for planning status) gives information about the planning status of an order.

In the beginning, the planning status will have a *white background* and shows you a point in time (in this example 08:22). This point in time is the latest pickup time (preferred delivery time - transport duration) when a truck should pickup the order, otherwise it would deliver late and you will receive minus points.

If the *background turns pink* it means that you have still 10 minutes until this latest pickup time. In this example the third order in the table should be picked up at the latest at 08:16. Since the background is pink, the current game time is 08:06 or later.

Once you have assigned a certain truck to an order, the planning status shows a *picture of this truck*. In this example the second order in the table has been assigned to the blue truck.

I want to change the sequence of the orders that I have assigned to a truck. How can I do that?

You cannot change an order-truck plan after you have pressed ”tell driver” button, you can also not change the sequence of the plans.

Appendix B: Measures and items for the survey

Intensity of DSS usage, adapted from Ahmad and Schroeder, 2001
(Measured on a 7 point Likert scale from (1) very much disagree, to (7) very much agree, in addition, we provided the answer category (8) we do not have this technology)
If a planners assigns routes to orders he always makes use of ...
... an electronic list (excel, transport management system, etc.) of routes
... an electronic list of orders
... an electronic list of drivers
... a software tool that enables to make good comparisons regarding ...
... efficiency (e.g. empty distance)
... punctuality
... travel and rest times of drivers
... profit
... a software tool that chooses the optimal solution

Planner-interdependence, adapted from Morris and Steers, 1980, and Price, 1997
(Measured on a 7 point Likert scale from (1) very much disagree, to (7) very much agree)
In order to do his job well, a planner needs to be able to get along well with other planners
The planning job requires that planners work closely together with other planners
Planners often take over orders from other planners
A planner can do his job only well, if other planners do that also
Planning is always being discussed in detail with other planners
Planners often take over drivers/routes from other planners

Planning satisfaction, adapted from Sanders and Courtney, 1985, and Lilien et al., 2004
(Measured on a 7 point Likert scale from (1) very much disagree, to (7) very much agree)
Route planning of the planning department is of high quality
I am satisfied with the decisions of the planning department
The route plans of the planning department are very efficient
The planning department makes transport related decisions fast
The performance of the planning department contributes greatly to profit

Planning criteria
(Measured on a 5 point scale from (1) important, to (5) extremely important, and, in addition, (6) not applicable)
Which criteria are important for constructing a tour?
Customer satisfaction (beside punctuality)
Punctuality
Profit of trip
Capacity utilization
Number used trucks
Empty distance

Reasons to invest in technology
(Respondents could tick several answers)
What are the most important reasons for your company to invest in planning technology?
better communication between planners, drivers and clients
better overview over planning (e.g. automatic reports)
higher capacity utilization rate
faster planning
less empty distance
more reliable working hour registration of drivers
more reliable planning
less planning mistakes
wish of client

more feasible planning
more trucks per planner
freight security
depend less on experience of planners
was a success for other companies (best practices)

Process characteristics, partially adapted from Golob and Regan, 2003
(Measured by open questions for which respondents could either give a value or a range which we then averaged.)
What is the percentage of orders for which planners participate in price negotiation?
How many shipments does a planner have per day on average?
How many drivers does a planner have per day on average?
How many addresses does a planner have per day on average?
How many route plans does a planner have per day on average?
What is the percentage of orders that planner receive on the day of execution before 10 o'clock?
What is the percentage of orders that planner receive on the day of execution after 10 o'clock?
What is the percentage of route plans changed during the day?
What is the average distance between pick up and delivery in km?
How many power units does your company have?
What percentage of trips is international?
What percentage of trips is temperature controlled?

Education level of average planner
(Measured by providing several actual Dutch education levels, which we translated and summarized to form the three answer categories given below:)
What is the highest level of education for the average planner in your company?
Preparation level for vocational school or less
Vocational school
Education at least preparing for advanced technical colleges or university

Additional in-company training
(Measured by answer categories given below:)
Was there additional education for planner and has the average planner been trained by it?
yes, training within our company
yes, vocational training
yes, both training within our company and vocational training
no

Planning effort, adapted from Price and Mueller, 1986, and Wall et al., 1995
(Measured on a 7 point Likert scale from (1) very much disagree, to (7) very much agree)
In order to prevent problems in their work, planners need very good knowledge of the transport process
Planners have to be very creative in their work
In order to prevent problems in their work, planners need very good knowledge of laws and regulations
Planners spend a lot of time thinking
Planners encounter often problems, for which the solution is not directly obvious
Every day planners learn something new

Formalization, adapted from Malhotra et al., 2001
(Measured on a 7 point Likert scale from (1) very much disagree, to (7) very much agree)
The job description of planners is...
... complete
... up-to-date
If there is a problem in planning we have a procedure to deal with it
Planing rules and procedures are explicitly documented
Comprehensive rules exist for all routine activities (duties and responsibilities)
There are significant penalties for planners violating procedures (item dropped after factor analysis)

Decentralization, adapted from Hage and Aiken, 1980, and Malhotra et al., 2001
(Measured on a 7 point Likert scale from (1) very much disagree, to (7) very much agree)
Planners are closely involved in all decisions related to ...
... new technologies for their job
... new personnel for the planning department
... organizational changes that have consequences for their way of working
... new drivers
Planners hire trucks from other transport companies autonomously
Planners work autonomously when they solve problems
Planners search contact autonomously with other transport companies in order to improve planning (e.g. avoid empty km)

Feedback, adapted from Ahmad and Schroeder, 2001
(Measured on a 7 point Likert scale from (1) very much disagree, to (7) very much agree)
Planners receive detailed feedback on their performance regarding ...
... punctuality
... driving and resting time of drivers
... profitability of trips
... empty distance
... gasoline usage
Planners receive daily feedback on the quality of their work
Planners always get compliments when they do their work well (item dropped after factor analysis)

Uncertainty, adapted from Chen and Paulraj, 2004
(Measured on a 7 point Likert scale from (1) very much disagree, to (7) very much agree)
The average amount of shipments varies to a great extent from one week to another
The average amount of required trucks varies to a great extent from one week to another
Drivers which are affected by our planning ...
... execute plans exactly
... deliver reliable performance
Planner can estimate the traffic density very well
Our trucks can always driven on well (absence of traffic jams)

Samenvatting (Summary in Dutch)

In 1832 werd het beslissingsprobleem van de handelsreizigers voor het eerst geformuleerd: vind de korste weg tussen een verzameling van steden, zodat je elke stad (of klant) éénmaal bezoekt. Het probleem van de handelsreiziger behoort tot een tak van de bedrijfswetenschappen die zich met wiskundige modellen bezighoudt en die vaak een groot aantal mogelijke oplossingen kent. Het probleem van de handelsreiziger wordt bijvoorbeeld met een toenemend aantal steden al snel te groot om de optimale oplossing binnen een afzienbaar tijdsbestek te kunnen vinden. De grens van dit optimalisatie vraagstuk ligt rond de 80 steden, zelfs met het gebruik van moderne computers. De algoritmen en modellen, die binnen deze tak van de bedrijfswetenschappen, Operations Research, ontwikkeld worden, kunnen in de besissingsondersteunende systemen ingebed worden. Hoewel deze systemen de bovengenoemde problemen sneller en nauwkeuriger dan mensen kunnen oplossen, worden ze in de praktijk nauwelijks gebruikt. Verbazingwekkend, gezien de hoge kosten die met deze beslissingen verbonden zijn. Om een voorbeeld te geven: bij Nederlandse transportbedrijven was in 2007 meer dan 60% van de kosten verbonden was met de vraag: "Welke route kan de vrachtwagen het beste rijden?"Men gaat ervan uit dat, hoewel technologie abstracte problemen beter kan oplossen dan de menselijke planner, wij altijd nog niet genoeg over de daadwerkelijke plansituatie weten om beslissingsondersteunende software te kunnen schrijven die dit potentieel ook daadwerkelijk waar maakt.

In dit proefschrift wordt het samenspel van technologie en vraagstukken voor het planningsproces bij transporteurs onderzocht. In de toekomst zullen steeds meer transporteurs over zogenoemde monitoringssystemen beschikken, de gegevens bijvoorbeeld per sateliet overdragen. De sneller beschikbare en nauwkeurigere gegevens maken het in principe mogelijk om snellere en betere beslissingen te kunnen nemen. Klanten van transportbedrijven, die over zulke monitoringssystemen beschikken, verwachten voorts dat zij opdrachten steeds later kunnen plaatsen. Zij verwachten dat zij kort voor of zelfs gedurende de uitvoering van een transportopdracht, deze nog kunnen wijzigen. Planners worden vaker in hun concentratie gestoord en krijgen misschien meer gegevens dan dat zij kunnen verwerken. Daarmee wordt het nog belangrijker dat planningstechnologie op menselijke denkprocessen wordt afgestemd. Daarbij is het beter, niet alleen denkprocessen in het algemeen, maar ook denkprocessen gedurende de uitvoering van logistieke planningsactiviteiten onder de loep te nemen. Om systematisch te onderzoeken hoe synergie effecten tussen mens en machine kunnen worden bewerkstelligd, worden in dit proefschrift vier mechanismen geïdentificeerd en getest om de samenwerking tussen taakstelling en de ondersteunende technologie in de context van planning binnen transportbedrijven te analyseren.

Deze dissertatie behoort tot het nieuw onstaande gebied van gedragsonderzoek binnen de bedrijfswetenschappen. Kort gezegd: terwijl de traditionele operations management onderzoekt welke raad men de planner het beste geven kan, analyseert dit proefschrift welke mechanismen daarvoor verantwoordelijk zijn hoe deze wetenschap ook in de praktijk benut kan worden. Dit proefschrift is gebaseerd op empirisch verworven gegevens, die met verschillende statistische methoden geanalyseerd zijn. In de eerste twee onderzoeken werd gekeken naar het effect van de weergavemogelijkheden op het planningsproces, zowel in de situatie dat de planners speciale beslissingsondersteunende systemen gebruiken, als ook de situatie dat ze de aangeboden data zelf verwerken. De data werden verzamelt met een experiment waarvoor een eigen software werd ontwikkelt en waaran 118 studenten deelnamen. In het derde en vierde onderzoek werd gekeken hoe de technologie in de praktijk van planners gebruikt werd en in hoeverre verscheidene organisatievormen van planningsafdelingen de mogelijkheid bieden om de planners te ondersteunen. Voor het derde en vierde deelonderzoek is een online vragenlijst ontwikkeld, die in totaal door 184 Nederlandse transportbedrijven is ingevuld.

Planningssoftware verbetert de planningsprestatie niet automatisch. Verschillen, betrekking hebbend op: tijdsdruk, de manier waarop een planner beslissingen neemt, de mate waarin een planner afhankelijk is van de samenwerking met andere planners en de organisatievorm van een onderneming beïnvloeden in hoeverre het potentieel van de planningstechnologie ook daadwerkelijk benut wordt. Deze dissertatie onderzoekt vier mechanismen waarmee planningsvraagstukken en technologie op elkaar afgestemd kunnen worden.

Zusammenfassung (Summary in German)

1832 wurde das Entscheidungsproblem des Handlungsreisenden zum ersten Mal dokumentiert: finde den kürzesten Weg um eine vorgegebene Menge von Städten jeweils einmal zu besuchen. Das Problem des Handlungsreisenden gehört zu einem Teil der Produktionswirtschaft der sich mit mathematischen Modellen befasst, die sich oft durch einen sehr grossen Lösungsraum auszeichnen. Zum Beispiel kann man eine optimale Lösung für das Problem des Handlungsreisenden nur für bis zu 80 Städte garantieren - auch unter zur Hilfenahme moderner Computer. Die Algorithmen und Modelle, die hierbei untersucht werden, können in sogenannte entscheidungsunterstützende Systeme eingebettet werden. Obwohl diese Systeme oben genannte Probleme weitaus schneller und genauer als Menschen lösen können, werden sie in der Praxis kaum gebraucht. Das ist umso erstaunlicher, als die entsprechenden Entscheidungen oft mit hohen Kosten verbunden sind. Zum Beispiel wurden im Jahr 2007 in holländischen Transportunternehmen mehr als 60% der Kosten durch Kraftstoff und Personalkosten verursacht aber nur 8.9% durch Abschreibungen. Man geht davon aus, daß Technologie zwar abstrakte Probleme effizienter lösen kann als Planer, wir aber immer noch nicht genug über die Planungssituation in der Praxis wissen, um entscheidungsunterstützende Software zu entwickeln deren Potential auch tatsächlich wahrgenommen wird.

Die vorliegende Arbeit erforscht die Abstimmung von Planungsaufgaben und -technologie in Transportbetrieben. In der Zukunft werden immer mehr Transportbetriebe über sogenannte Monitoringssysteme verfügen, die detaillierte Daten über den Stand der Transportausführung liefern können und somit prinzipiell schnellere und bessere Entscheidungen ermöglichen. Kunden von Transportbetrieben, die solche Monitoringssysteme verwenden, erwarten, daß es möglich ist Aufträge zu immer späteren

Zeitpunkten zu platzieren und sie kurz vor oder sogar während der Ausführung von Transportaufträgen abzuändern. In Transportbetrieben die solche Echtzeitdienstleistungen anbieten, werden Planer dann häufiger in ihrer Konzentration gestört und erhalten womöglich mehr Daten als sie verarbeiten können. Es wird somit wichtiger daß Planungstechnologie auf menschliche Denkprozesse abgestimmt wird. Hierbei ist es von Vorteil speziell Denkprozesse während des Ausführens von logistischen Planungsaktivitäten unter die Lupe zu nehmen. Um mögliche Synergieeffekte zwischen Mensch und Maschine systematisch zu erforschen, identifiziert und testet die vorliegende Arbeit vier Mechanismen für die Abstimmung von Planungsaufgaben und -technologie im Kontext von Transportbetrieben die Echtzeitdienstleistungen anbieten. Diese Dissertation gehört somit dem neu entstehenden Bereich der Verhaltensforschung innerhalb der Produktionswirtschaft an. Während traditionelle Produktionswirtschaft der Frage nachgeht, welchen Rat man einem Planer geben soll, erforscht die vorliegende Arbeit welche Mechanismen dafür verantwortlich sind, dieses Wissen auch in die Praxis einfliessen lassen zu können.

Die vorliegende Arbeit basiert auf empirisch erhobenen Daten, die mit unterschiedlichen statistischen Methoden analysiert wurden. Die ersten beiden Studien erforschen den Effekt von Darstellungsmöglichkeiten auf Planungsprozesse - sowohl für die Fälle wenn Planer spezielle entscheidungsunterstützende Systeme in Anspruch nehmen, als auch wenn sie die elektronisch angebotenen Daten selbst bearbeiten. Die Daten wurden im Rahmen eines Experiments und unter zu Hilfenahme einer eigens entwickelten Software erhoben. Insgesamt 118 Studenten nahmen an dem Experiment teil. Die dritte und vierte Studie beschäftigen sich damit wie Planungstechnologie in der Praxis von Planern genutzt wird und welche Einfluss verschiedene Organisationsformen von Planungsabteilungen haben. Hierfür wurde ein Online Fragebogen entwickelt, der von insgesamt 184 holländischen Transportbetrieben ausgefüllt wurde.

Planungstechnologie verbessert Planungsleistung nicht automatisch. Unterschiede bezüglich Zeitdruck, der Art wie Planer Entscheidungen treffen, dem Ausmaß indem Planer in ihren Entscheidungen von der Zusammenarbeit mit anderen Planern abhängig sind, und Organisationsformen beeinflussen inwieweit das Potential von Planungstechnologie auch tatsächlich genutzt wird. Diese Dissertation erforscht vier solcher Mechanismen um Planungsaufgaben und -technologie aufeinander abzustimmen.

About the author

Elfriede Irene Krauth was born on december 29, 1976 in Köln, Germany. During her secondary education at the Gymnasium der Englischen Fräulein, Bamberg, Germany, Elfriede spent one year at Castle High School in Newburgh, IN, USA. In September 1996, Elfriede started her degree of Business Informatics at the Mannheim Universität, Mannheim, Germany. In 1999, she went on a five month exchange to the Universidad de Belgrano, in Buenos Aires, Argentina. Elfriede wrote her master thesis on "Synergy Potential of a Logistic Process Chain of a Multi-channel Retailer - illustrated at the example of KarstadtQuelle AG". During her time as student, Elfriede supervised students on the development of software projects. She was also working as a software developer herself in a transport company and a consulting company. When Elfriede was going from her university town to her parents place by train she passed the following cities, which are the beginning of the first description of the traveling salesman problem, documented in 1832 (Applegate et al., 2007): Frankfurt, Hanau, Aschaffenburg, Würzburg, Schweinfurt, Bamberg.

After her studies, Elfriede received a studentship to work as a teaching assistant at the Universidad de Navarra, Pamplona, Spain. In Pamplona, Elfriede worked together with José Antonio Alfaro Tanco. She conducted a literature survey and participated in a case study of the application of the SCOR model for small and medium enterprises. In Pamplona Elfriede also received a Certificate on European Studies. In September 2003, Elfriede started her PhD project at the Erasmus Institute of Management, Rotterdam School of Management under the supervision of Prof.dr. Steef van de Velde and Prof.dr. Jos van Hillegersberg. Her project was financed by DEAL (distributed engine for advanced logistics). Her teaching experience includes two bachelor thesis courses on Leaping Logistics and Roaring Retailing.

In the beginning of 2006, Elfriede spent a research visit at the Helsinki University of Technology, Finland where she was working with Prof.dr. Jan Holmström and taking a class on ”Internet technologies for mobile computing” from Prof.dr. Kimmo Raatikainen, senior architect for Nokia Technology Platforms.

Elfriede has presented her work in Montréal, Canada (Pre-ICIS workshop on HCI research 2007), Hawaii (Hawaii International Conference on System Sciences 2007), Riezlern, Austria (CEMS Seminar on European Supply Chain Management 2005-2008), Glasgow, UK (European Operations Management Association 2006), Budapest, Hungary (European Operations Management Association 2005), Barcelona, Spain (International Conference of the DSI 2005), Fontainebleau, France (Doctoral consortium of the European Operations Management Association 2004), and in St. Eloi, France (Doctorate Workshop of the European Logistics Association 2004).

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REAL-TIME PLANNING SUPPORT
A TASK-TECHNOLOGY FIT PERSPECTIVE

Planning technology by itself is not sufficient to improve planning performance. Low adoption rates of specific planning software indicate that we not only need to know what advice to give to planners, but also how to give it. What factors determine how planners interact with technology as they carry out their task? In order to answer this question, this dissertation studies four mechanisms of fit between task and technology based on results both from the laboratory and a survey conducted in the Dutch transport sector.

We specifically focus on the transport context as, on one hand algorithms supporting the planning task are extensively studied, and on the other hand, they are used in practice to a low extent. Apparently, task and technology do not fit. We contend that task-technology fit becomes more important as planning has to provide real-time services. Planners need technology that better fits their information processing, and solution quality of specialized algorithms benefits from the assistance of human planners for assessing volatile customer demand.

Our results indicate that data presentation structure and presentation of specialized algorithms can influence the decision making process. Providing functionality for collaborative optimization in addition to functionality for isolated optimization can further increase the extent to which planners make use of specialized planning technology. In addition, this thesis examines the human factor in planning, specifically the role of interdependence between planners, decision making style of planners and organizational structure.

The practical implications of this dissertation are of interest mainly for managers in transport and transport software companies. The theoretical contribution relates to the field of Behavioral Operations Management.

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