THE AI PLANNER OF THE FUTURE

AI-enabled decision-making in Supply Chains and Logistics

Prof.dr. Tom Van Woensel (Program leader)

The AI PLANNER OF THE FUTURE research program is hosted by the Department of Industrial Engineering & Innovation Sciences and is supported by the European Supply Chain Forum, Department of Industrial Engineering & Innovation Sciences, the Eindhoven Artificial Intelligence Systems Institute, the Logistics Community Brabant and the TKI Dinalog. The program connects to the different communities, moonshots strategic agendas and the themes of each of these supporting partners. It combines 25 researchers, 10 PhD students and over 50 Bachelor and Master students, for the coming five years (2021-2026). The research program is explained in detail below, including the 10 individual PhD projects.

Setting the scene

The Internet of Things enables the instant exchange of data and information between machines, operators, and organizations. As such, supply chains benefit from an instant exchange of information on inventory availability, supply conditions, etc. Corrective and scheduled maintenance becomes condition-based and predictable, while Digital Twins are used to further optimize production- and maintenance processes. All these evolutions allow to optimize the performance of the key operational processes eventually leading to improvements on both internal (i.e., efficient, and effective processes) and external objectives (i.e., customer value, competitive advantages).

However, although promising, transforming the traditional supply chains and logistics, and their operations (manufacturing, transportation, order fulfillment, inventory, etc.), to fully reap the benefits is challenging. That is, decision-making in Supply Chain and Logistics is complex and different from decision-making in other areas as it involves many intertwined multi-disciplinary decisions (think of transport, inventory, location, human resources, ICT systems, etc.) and key performance indicators (including people, profit, planet dimensions and also ethics and corporate social responsibility).

The quintessential dream of Artificial Intelligence (AI) for automated planning (in supply chain and logistics) is to create a world without any human planners. All planning operations and tasks, all feedback, all data is processed automatically by advanced algorithms. Thus, everything is done completely automatically, and autonomously, without the need for any human intervention. Along the same lines, McKinsey (2018) coined the notion of no-touch planning, aiming to eliminate the role of humans in planning as people only add error (as compared to a completely data-driven planning process). This line of reasoning often leads to popular "consultancy-like" quotes as:

Planning as we know it, is dead - Frank Calderoni [1]

The AI PLANNER OF THE FUTURE research program explicitly does not follow this mainstream techno-vision of *AI replacing humans*.

[1] https://www.computereconomics.com/article.cfm?id=2492

This AI PLANNER OF THE FUTURE program considers the explicit intertwining of technical and human elements in the context of AI planning for supply chains and logistics, considering all relevant performance indicators (people, profit, and the planet).

Hence, we aim to leverage the AI benefits without completely replacing the essential element of knowledgeable human beings. The proposition that people only add error is false, but one needs to identify when people make predictable mistakes and when they are predictably better than purely data-driven models. This necessitates knowledge from a multidisciplinary point of view, but also challenges the current AI research domain. Explainable AI, trustable AI, ethics and the needed algorithms need to be generated or adapted to the planning domain, applied in a supply chain and logistics setting.

Planning complexity

Our perspective on AI supply chain and logistics planning is a unique approach that is highly relevant for businesses and academia and calls for different methodological approaches than the classical AI planning approaches so-far. While there is quite some practical evidence of working AI-enabled environments, e.g. smart thermostats, home service robots, intelligent conversational chatbots, autonomous drones, or even self-driving cars, decision-making in Supply Chain and Logistics is complex and different from decision-making in these areas.

Processes within supply chain and logistics environments are highly complex, interdependent, and intertwined. Increasing process efficiencies lead to improved agility and transparency in the supply chain. These efficiencies are e.g. enabled by advanced analytics, AI, and blockchain. As such, supply chain and logistics data are activated and used to proactively mitigate disruption and simplify these processes. Moreover, enabled by (real-time) data, supply chain visibility on the order process, inventory, delivery, and potential supply chain disruptions is facilitated. Advanced embedded AI capabilities provide real-time intelligence and actionable planning recommendations. This research program also focuses on the inclusion of harder to measure concepts such as human (interaction), sustainability, and ethical concerns as a driving force for AI planning, creating a distinct perspective and following recent calls in the literature (e.g. Sanders *et al.* 2019). The Human In-The-Loop (HITL) versus the Human Out-of-The-Loop (HOTL) situation is an important planning aspect to be considered here as well. Note that not only monetary aspects are important (e.g. cost reductions) but it is also important to investigate (if and) how AI enables supply chains and logistics to make a major contribution towards reducing greenhouse gas emissions (Dauvergne 2020) and the sustainability element of companies' Corporate Social Responsibility (CSR) agenda.

The role and contribution of AI to classical planning is identified as a key AI application domain before but has remained "a largely unsolved core AI competency due to the complexity of the tasks both in terms of representation as well as reasoning" (Sreedharan et al. 2020). We address this gap by alleviating the complexity of fully automated reasoning with abundant human expert and domain knowledge, leading to AI-enabled decision-making and support systems, with a focus on Supply Chains and Logistics.

Concluding, planning as we know it is certainly dead, but **we envision the planning "nouveau" to be a "hybrid" form of decision-making in which both human- and artificial intelligence are combined**, able to properly handle this complexity within supply chains and logistics.

Autonomy, what's in a name?

In their Harvard Business Review article, Porter and Heppelmann (2014) discuss four stages within an internet of things setting. We use these stages to discuss the intelligence of *decision support systems* for planning tasks.

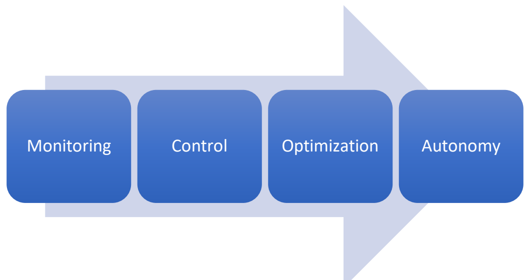

Figure 1. The four stages of AI-enabled planning

Every company and process need to move through all stages shown in Figure 1 to move towards more autonomy in its decision-making.

- *Monitoring* involves following the status of several connected and complex logistics and supply chain systems and environments. Where are my resources, are they in time, what is the status of a certain production system, etc.? This information is typically available in various sources, ranging from advanced ERP systems to individual planners (tacit knowledge).
- *Control* is done via algorithms (ranging from rules-of-thumb to advanced decision algorithms). These are rules that direct the system to respond to specified changes in the environment. For example, if a truck is late for a customer, which action should be taken to resolve this?
- Combining monitoring and control leads to effective ***optimization*** embedded in the decision support systems. This latter is typically the field of Operations Management and Operations Research, including machine learning and data analytics.
- Ultimately, monitoring, control, and optimization lead to a certain level of ***autonomy***. Systems function with a certain degree of autonomy, applying algorithms that utilize (real-time or historical) data about their performance and its environment, which eventually leads to efficient automated planning of supply chain and logistics processes.

With regards to the latter stage, **choosing the appropriate level of *Autonomy*** is key to the optimal inclusion of AI in supply chain and logistics processes. The challenge is to use a complete AI-enabled decision support system where that is doable and optimal but sticking to lower level AI-enabled decision support when necessary (Muller, 2012). Like the 5 levels of autonomous vehicles, it is necessary to identify such levels for autonomous AI supply chain and logistics and to outline a road map towards AI planning full autonomy (as in Level 5: Full Automation for vehicles). Along this continuum, various questions related to the interaction between the human decision-makers and the computer are relevant (e.g. under which conditions will the

AI planner be able to take over? When to overrule human decisions or AI planner decisions?) The answers to these questions might not be the same for different industries and supply chain and logistics operations. Some AI planning processes might need to be on the highest level of automation, while others might provide good performance with proper human intervention only.

Relevant Artificial Intelligence challenges arise in every stage (i.e. monitoring, control, optimization, and autonomy). Collecting, managing data, and track-and-trace, also in real-time, are difficult challenges (*monitoring*). Next to Information systems aspects (e.g. blockchains, or anonymization), also issues in terms of privacy, trustworthiness, and data sharing considerations need to be handled properly. Also, it is challenging to extract useful knowledge from collected data with machine learning methods such that they can be integrated with control to augment optimization. The phases *control* and *optimization* lead to various questions related to algorithm-building often in real-time (as such reducing the time between plan and execution). Also working towards proper engineering solutions (e.g. manufacturing, personalized medication, or mobility solutions) that can cope with high-complexity situations are key success factors.

The individual PhD projects

Within the setting of decision-making where both human- and artificial intelligence interact and meet each other, we defined 10 individual PhD projects. These Phd projects mostly combine expertise from different fields and explicitly connect to the different communities and focus areas of the European Supply Chain Forum, the moonshots and the strategic agenda of EAISI, the themes of the LCB and the TKI Dinalog.

The broadness of the supply chain and logistics **application domains** are very visible in the areas covered in the individual PhD projects: Marketing-Operations Interface (Project 1, 5), Customer demand and interaction (Project 1, 5), Forecasting (Project 1, 2), Industry 4.0 (Project 2, 9, 10), Omnichannel supply chains (Project 3), Inventory management (Project 2, 3), Customer fulfilment (Project 3), Freight transport and mobility (Projects 3, 4, 6, 7), perishable supply chains (Project 4), Production (Project 4, 5), Servitization (Project 5), high-tech industry (Project 8), healthcare (Project 8).

Methodologically, we will contribute to the following domains: Actionable and explainable AI and decision support (Project 1), Human-AI collaboration (Project 2, 8), Deep reinforcement learning, neural networks and machine learning (Projects 3, 4, 7, 8), data anonymization (Projects 3, 9), Data-driven robust and online optimization and heuristics (Project 4, 7, 8), Kernel-based classifications (Project 4), digital twins (Project 5, 7), Augmented Reality (Project 5), policy evaluation (Project 3, 7), Trustworthy AI (Project 9), AI Ethics (Project 10).

Our consortium: Experts from practice and academia

Classical planning is everywhere and thus this research program is relevant for all different stakeholders across the supply chain (e.g., the focal company, individuals within the company, other companies). All industries are involved: fast-moving consumer goods, omnichannel retailing, last-mile logistics, services, health, transport and mobility, high-tech industries, etc. Moreover, AI planning covers many research domains: inventory, operations management/research, human-technology interaction, ethics, information systems, sustainability, marketing, servitization, etc.

The AI planner of the future program needs a broad range of research fields and a rich set of involved companies. We have both. This research program combines the **extensive knowledge of researchers from all multi-disciplinary IE&IS domains** and the real-life living labs of **European Supply Chain Forum companies** from diverse industries. It connects to various other programs and institutes (EAISI, LCB and TKI Dinalog).

The **European Supply Chain Forum** (ESCF) works with over 60 leading global players sharing problems and insights related to Supply Chain Management and logistics. Over the years, it became the prime ecosystem of multi-disciplinary professionals interested in operations, logistics, and supply chain management. The unique value of ESCF is that it combines talent, knowledge, and network in one ecosystem. The ESCF ecosystem extends into several dedicated communities: Data2Move, ESCF High Tech Community (EHTC), Fast Moving Consumer Goods (FMCG), and Servitization. Companies pay a subscription fee that supports the talent, knowledge, and network triangle. The ESCF ecosystem is the **ideal field lab** for the AI PLANNER OF THE FUTURE program.

The Department of **Industrial Engineering and Innovation Sciences (IE&IS)** at the Eindhoven University of Technology (TU/e) aims at being a European frontrunner in research and education on how to develop and implement technology in industry and society responsibly and effectively. Research and education at the department focuses on gaining knowledge on and designing solutions for complex industrial and societal challenges, combining its rich range of in-house disciplinary perspectives from the technical sciences, social sciences, and humanities. The AI PLANNER OF THE FUTURE research program directly connects to all four departmental research themes: Logistics and its Interfaces, Value of Big Data, Sustainability and Humans & Technology.

The **Eindhoven Artificial Intelligence Systems Institute** (EAISI) builds up an integrated system view on AI in a multidisciplinary institute, with key contributions from three key domains: Data Science, Humans and Ethics and Engineering Systems. The AI PLANNER OF THE FUTURE research program connects, through its various PhD projects, a large number of EAISI moonshots, like the Thinking Assistant (all projects), NextGen Industry (projects 2, 5 and 8), Trustworthy Data (project 1, 2, 7, 9 and 10), Responsible Mobility (projects 3, 4, 6 and 7), and Zero Waste Industry (projects 4, 6 and 7). Additionally, this program fits very closely to the Artificial Intelligence Scientific Roadmap. More specifically, the following research program lines are of importance for our individual projects: Decision-making for Engineering Systems, Augmenting Intelligence, Certifiable, Robust, and Explainable AI, Trustworthy Data Integration, Merging Models and Data in AI, and Augmenting Intelligence. These links are explained in more details in the individual PhD projects.

The **Logistics Community Brabant** (LCB) as a large collaboration between the Technische Universiteit Eindhoven, Universiteit van Tilburg, Nederlandse Defensie Academie and Breda University of Applied Sciences, also serves as an important pilot and demonstrating environment, more specifically for the Small and Medium-sized enterprises. The AI PLANNER OF THE FUTURE research program also is relevant for the following LCB themes: Data-driven logistics (data-gedreven logistiek), the sustainable city (leefbare stad), multimodal (multimodaal) and Smart Industry. Companies in the LCB network will have the opportunity to collaborate with the researchers in the PhD projects and host the Master students involved.

TKI Dinalog is the relevant top consortium for knowledge and innovation in which companies, knowledge institutions and government work together on the innovation program for the Top Sector Logistics. The AI PLANNER OF THE FUTURE research program contributes directly to several themes such as supply chain management, E-commerce, Cross Chain Control Centers, Urban logistics, and synchromodal.

References

Müller, V.C. Autonomous Cognitive Systems in Real-World Environments: Less Control, More Flexibility and Better Interaction. Cogn Comput 4, 212–215 (2012).

McKinsey (2018), The route to no-touch planning, https://www.mckinsey.com/business-functions/operations/our-insights/the-route-to-no-touch-planning#

Porter M. E. and Heppelmann, J. E. (2014). "How Smart, Connected Products Are Transforming Competition", Harvard Business Review, 92, pp. 11-64.

Sanders, N.R., Boone, T., Ganeshan, R., and Wood, J.D., 2019. Sustainable Supply Chains in the Age of AI and Digitization: Research Challenges and Opportunities. *Journal of Business Logistics*, 40 (3), 229–240.

Sreedharan S., T. Chakraborti, C. Muise and S. Kambhampati (2020), Expectation-Aware Planning: A Unifying Framework for Synthesizing and Executing Self-Explaining Plans for Human-Aware Planning, AAAI

The ESCF companies involved in the AI PLANNER OF THE FUTURE research program

Researchers involved in the AI PLANNER OF THE FUTURE research program

Name	Function	Group	Discipline
Floor Alkemade	HL	TIS	Mobility
Zumbul Atan	UHD	OPAC	Supply Chain Management
Frauke Behrendt	UHD	TIS	Mobility
Laurens Bliek	UD	IS	Artificial Engineering, Machine Learning
Remco Dijkman	HL	IS	Information Systems
Dirk Fahland	UHD	M&CS	Computer Science
Sarah Gelper	UHD	ITEM	Marketing Analytics
Fred Langerak	HL	ITEM	Product Development & Management
Pascale Le Blanc	HL	HPM	Workplace Innovation and Sustainable Employability
Ahmadreza Marandi	UD	OPAC	Robust Optimization
Vincent Müller	HL	P&E	Philosophy
Nevin Mutlu	UD	OPAC	Revenue Management
Neomie Raassens	UHD	ITEM	Servitization
Sonja Rohmer	UD	OPAC	Logistics/ Food supply chains
Gerrit Rooks	UD	HTI	Adoption of (technological) Innovation, Contextual psychology
Jeroen Schepers	UHD	ITEM	Frontline Service and Innovation
Albert Schrotenboer	UD	OPAC	AI and Transportation
Chris Snijder	HL	HTI	Decision-making, Trust, Human-Data Interaction
Anna-Sophie Ulfert	UD	HPM	Organizational Behavior and AI
Phillipe Van de Calseyde	UD	HPM	Decision Making
Willem Van Jaarsveld	UHD	OPAC	Operations, Planning, and Control
Tom Van Woensel	HL	OPAC	Freight Transport & Logistics
Martijn Willemsen	UHD	HTI	Human-Data Interaction, Explainable AI
Carlos Zednik	UHD	P&E	Philosophy
Yingqian Zhang	UHD	IS	Artificial Engineering, Machine Learning

HPM: Human Performance Management, HTI: Human-Technology Interaction, IS: Information Systems, ITEM: Innovation, Technology, Entrepreneurship and Marketing, OPAC: Operations, Planning, Accounting and Control, P&E: Philosophy and Ethics, TIS: Technology, Innovation and Society.

Project 1: Learning about Customers: Demand Implications of Logistics-Related Decision-Making in B2B
PIs: Gelper, Mutlu, Langerak

In business-to-business (B2B) exchanges, customers are more likely to buy from suppliers who know them well and consistently provide good service. Yet, when planners optimize the operations with a focus on cost-reduction, they risk overlooking the importance of building long-term relationships with their customers. These relationships critically depend on learning the customer's preferences, priorities, and service expectations. While building strong customer relationships in a B2B context has traditionally been the salespeople's responsibility, AI developments now open the possibility for AI-based learning about customers. AI-based learning about customers in a B2B setting is complex though because each customer has their own needs and preferences, leading to highly customized offerings. These customized offerings often include agreements on critical logistics-related decisions such as lead times, delivery, and maintenance planning. In this setting, close contact between the people from sales and operations – i.e., a strong marketing-operations interface – benefits the customer relationship. Yet as information on customers is embedded both in IT systems (e.g., CRM systems) and people (e.g., salespersons), this is a domain where B2B firms can benefit greatly from AI. This PhD project thus studies on how AI can help planners tailor their operations to better serve customer needs.

Project 2: Context matters: optimizing shared decision making in real-world forecasting and inventory management
PIs: Le Blanc, van de Calseyde, Ulfert

In many organizations and across industries, artificial intelligence (AI) is transforming the way we work. AI-systems are implemented to assist employees with decision making, to decrease workload, or to increase efficiency. Although promising, transforming traditional operations into ones that rely on autonomous systems brings many challenges. For example, when using AI planning systems, users frequently experience difficulties in using and trusting these systems and, as a consequence, deviate from their advice. Prior research highlights the impact of system characteristics (e.g. reliability) on human-AI collaboration. However, these studies disregard the important influence of contextual factors on human-AI collaboration. Therefore, one important challenge concerns the consideration of contextual factors when designing and implementing AI-systems at work. To successfully integrate these systems in organizational processes, it is critical to understand when and why users are (un)willing to adopt these systems in their work routines and how we can stimulate effective usage. The goal of this PhD-project is to address these issues by answering the following research questions: (1) Which contextual factors, specifically organizational (e.g. organizational climate, leadership) and societal factors (e.g. COVID-19 pandemic), impact planners' willingness to use AI planning systems? (2) How can human-centered AI and work design help to improve human-AI collaboration?

Project 3: AI-Based Replenishment and Order Fulfillment Strategies for Omnichannel Supply Chains
PIs: Atan, Schrotenboer, Van Woensel

While retailers are investing heavily in integrating online channels to their traditional offline channels, only a few giant players' efforts are profitable. The main problem is the failure to integrate essential operations of online and offline channels. To tackle this problem, this PhD research provides a real-time, data-driven AI-based planning strategy by integrating the decisions on three cornerstones of omnichannel retail: 1) inventory replenishment policy, 2) customer fulfilment policy, and 3) consumer delivery options and prices. We provide a new AI-based methodology to enable the real-time integrated control of these three cornerstones. Our study provides the omnichannel retailers with decision support tools that tell them when and where products in the supply chain should be replenished and stored and how customer orders should be fulfilled. In this way, we identify profitable omnichannel business models that will help these businesses to stay alive in the e-commerce market.

Project 4: Robust data-driven sustainable food supply chain
PIs: Marandi, Rohmer, Van Woensel

Food supply chains contain different types of uncertainty; from quality of supplied material to traffic congestion in last-mile delivery. These uncertainties often result in food losses and waste, aggravating the environmental footprint of the chain. As such, there is a need for robust policies that can address this uncertainty. Recently, we have seen how machine learning techniques, such as Neural or Kernel-based classifications, are used in Robust Optimization to derive robust policies by extracting important information from historical data. However, the computational complexity of these approaches remains an issue. In this project, we want to build on this recent stream of research and design approaches in data-driven robust optimization capable of tackling problems arising in food supply chain settings. By using machine learning techniques within the framework of robust optimization we intend to then design robust policies that mitigate the negative effects of uncertainties within the food system.

Project 5: Digital Twins: An ingenious AI companion or an evil twin?
PIs: Raassens, Schepers, Van Woensel

Digital twinning and remote visualization technologies rapidly gain popularity for the design and maintenance of (complex) production systems. Digital twinning is not a new term but paired with advancements in artificial intelligence (AI) and augmented reality (AR), it is increasingly valuable in transforming industrial operations, which, in turn, leads to the creation of additional business value. Digital twinning involves embedding sensors in Internet-of-Things-connected, complex industrial machines and applying artificial intelligence and machine-learning algorithms to the resultant big data. A sophisticated visualization of the machine allows remote engineers to proactively optimize productivity, reduce maintenance cost, and extend product life cycles. Although proactive actions make the manufacturer seem "closer" to the customer's business than ever before, paradoxically, the remote elements in digital twinning limit real-life customer contact that is needed to build loyal customer relationships and to gather ideas for new and improved products. Hence, while digital twinning can be an ingenious companion in optimizing operational decisions, it may also act as an evil twin that hampers marketing and innovation outcomes. Manufacturers need a solution for this pressing issue, but current literature has not yet considered the potential dark side of digital twinning in an interdisciplinary manner.

Project 6: AI for sustainable last-mile delivery by micromobility: a socio-technical perspective
PIs: Behrendt, Alkemade
This project aims to understand the opportunities and context of using AI for last-mile delivery by micromobility, contributing to innovating sustainable urban logistics and reducing carbon emissions. A particular focus will be on active micromobility such as cargo-ebikes.

Project 7: Data-driven Optimization using Digital Twins for Sustainable Last-Mile Delivery
PIs: Zhang, Bliek, Van Woensel

Due to the complexity of modern supply chains, it is difficult to predict what the effect will be of a decision aimed at reducing greenhouse gas emissions, such as choosing the location of a pick-up point, or changing the travel route for a vehicle. Digital twins make it possible to try these decisions in a virtual environment before applying them in real life. This helps policymakers in governments and companies gain a better understanding of the consequences of a decision, which reduces the risks and uncertainties of the radical new decisions that are necessary to achieve the sustainable supply chain of the future. With the rise of digital twins for smart cities, such as the Atlas Livable City developed by the Logistics Community Brabant, more data is readily available than ever before. Yet most existing optimization techniques, which are necessary for minimizing an objective such as travel time or greenhouse gas emissions, are not able to deal with such complex virtual environments. Data-driven optimization techniques are therefore an active area of research. Examples of this are optimization heuristics learned with machine learning, and surrogate models for optimization. This project will contribute to this active research landscape by making data-driven optimization techniques that are suitable for digital twins. The main application is the reduction of greenhouse gas emissions in last-mile delivery by choosing the locations of pick-up points in urban environments.

Project 8: Online Supply Chain Planning
PIs: Dijkman, Van Jaarsveld

Project Supply chain planning is complex because of complex dependencies of the delivery of the final product on the timely shipping, assembly, production, and procurement of its parts. Periodic supply chain plans are made. However, during the execution of the plan, it must often be adapted, for example, because parts are delivered late or because production is delayed. This leads to changes to the plan that are often ad-hoc and suboptimal, and cause planning 'nervousness', i.e. frequent planning changes. Consequently, in addition to periodic planning, supply chain planning can benefit from planning techniques that assist with the day-to-day adaptations of the supply chain plan, due to the unexpected situations that arise. These 'online' planning techniques must take the current periodic plan into account, as well as the current status of the procurement, production, and assembly of the parts. It should then advise on changes to the plan, while minimizing planning nervousness and costs. In this project we aim to develop such a technique for online supply chain planning, using novel techniques from the area of artificial intelligence that can learn to predict – based on the current situation and unexpected events that must be handled – what the best solution is to plan for the unexpected event. A general framework for these techniques is being developed in a related project, where applications in production and transportation planning are studied. The aim of this project is to make this general framework suitable for supply chain planning. Against this background, the project has a specific focus on encoding and learning the complex relations and patterns of dependency between different activities in supply chain planning, which to the best of our knowledge has not been studied before.

Project 9: From feared competitor to trusted companion: understanding and enhancing trust in AI over time

PIs: Snijder, Rooks, Willemsen

Artificially Intelligent systems are becoming both much more pervasive and better. The interaction between the human planner and AI systems is far from hassle-free, though: on the one hand, AI-generated decisions are not trusted and overridden when they should have been left alone. On the other hand, AI-systems are trusted when they should not have been. The literature has suggested several factors that influence the trust that a planner has in AI systems. Some of those factors are related to the planner (experience and expertise, for instance), some related to the system (transparency, reliability, fairness, …), and some related to the context in which the interaction takes place (high-risk vs. low-risk decisions, complex vs. more standard). An overlooked issue is that in many organizations, planners interact with the AI system repeatedly. This causes that, as planners interact more often, how they feel about and behave towards the system becomes more and more dependent on their experience with the system (and less dependent on these more often studied initial factors). This project focuses on trust in AI-systems over time and how past interactions of the planner with the AI-system shape future interactions.

Project 10: Widening the frame: Rational choice beyond a given utility function

PIs: Müller, Zednik , Fahland

Supply chain and logistics planning problems can be seen as optimisation problems that require collecting as much relevant information as possible, determining possible choices, and selecting the action with the highest expected utility. They thus lend themselves to AI solutions: "AI has adopted the standard model: we build optimising machines, we feed objectives into them, and off they go." (Russell 2019, 172). "Rational choice" in this sense assumes a given utility function. But apart from well-known problems with rational choice in real-world environments (e.g. uncertainty, dynamic changes, other agents, non-discreteness of actions), we know from the human example that highly complex choices in real-world environments require considering which utility function to use, e.g. whether the utility function used needs to change or be overruled. Humans are able to change the frame of reference and include additional factors (e.g. the health of employees) or even to conclude that maximal expected utility is not the right criterion (e.g. because an action would be unjust). The supply chain and logistics planning problems are a fine place for a case study of this frame problem in a practical environment: When and how can a system say: "I should not decide this with my given utility function, I should change the frame"?

1. Title of the PhD project

Learning about Customers: Demand Implications of Logistics-Related Decision-Making in B2B

2. Brief summary of the main research issue (max. 200 words)

In business-to-business (B2B) exchanges, customers are more likely to buy from suppliers who know them well and consistently provide good service. Yet, when planners optimize the operations with a focus on cost-reduction, they risk overlooking the importance of building long-term relationships with their customers. These relationships critically depend on learning the customer's preferences, priorities, and service expectations. While building strong customer relationships in a B2B context has traditionally been the salespeople's responsibility, AI developments now open the possibility for **AI-based learning about customers.**

AI-based learning about customers in a B2B setting is complex though, because each customer has their own needs and preferences, leading to highly customized offerings. These customized offerings often include agreements on critical logistics-related decisions such as lead times, delivery, and maintenance planning. In this setting, close contact between the people from sales and operations – i.e., a strong **marketing-operations interface** – benefits the customer relationship. Yet as information on customers is embedded both in IT systems (e.g., CRM systems) and people (e.g., salespersons), this is a domain where B2B firms can benefit greatly from AI. This PhD project thus studies on how AI can help planners tailor their operations to better serve customer needs.

3. Composition of the research group

Name, title(s)	Role (promotor/ (daily) supervisor/	Discipline	To the account of	Hours / week
dr. Sarah Gelper	Co-promotor / daily supervisor	Marketing Analytics	TU/e ITEM	4
dr. Nevin Mutlu	Co-promotor / daily supervisor	Revenue Management	TU/e OPAC	4
Prof. dr. Fred Langerak	Promotor	Product Development & Management	TU/e ITEM	1

4. Description of the project (1-2 pages)

4.1 Specification of the main research problem (i.e., key research problems and research aims)

This project contributes to the **marketing-operations interface** by answering the following questions in a B2B context:

(1) How can AI be used to learn about customers? How to learn from information embedded in IT systems (e.g., CRM) and people (e.g., salesforce), and how to integrate these two?
(2) How can the learned insights be translated into actionable decision support in day-to-day operations for planners?
(3) How can the learned insights be translated into actionable decision support for the design of logistics services?

4.2 Scientific importance and relevance of the project (i.e., innovative aspects, embedding in literature, added-value)

The importance of customer relationships has long been recognized in the marketing literature, yet operational costs are often ignored. Similarly, reducing cost has traditionally been the focus in the operations literature, yet the demand-implications are typically not accounted for. Recently, analytical work in revenue management illustrated that ignoring long-term customer value can lead to policies that perform "arbitrarily poorly" (Calmon et al., 2021). Likewise, accounting for the long-term impact of logistics-related decisions requires understanding the impact of today's operations on customers' future demand – i.e., it requires learning about customers. In today's B2B markets, building customer relationships goes well beyond setting the right price, as testified in a recent DHL report:

> ***"Customer experience surpassed price as the key differentiator for B2B buyers."***
>
> *– DHL (March 2021)*

This PhD project deals with AI-based learning about customers in a B2B context. As customers are trying to reduce the number of suppliers they buy from (known as "supplier consolidation"), manufacturers need to find new ways to gain and sustain key supplier status (Ulaga & Eggert 2006). A promising way to do so is by investing in learning about customers and using this knowledge to build close customer relationships. This project focusses specifically on the demand implications of logistics-related decisions. Some of these decisions are at the day-to-day operational level, e.g. decisions on inventory replenishment or order shipping, while others require redesigning the logistics service offerings including promised lead-times, shipping agreements, and traceability.

Recently, many advances have been made in learning about customers in the B2C context, particularly in retailing (see Chen et al. 2021, Martinez de Albeniz et al. 2020, and Bastani et al. 2021). However, learning about customers in B2B is different for at least two reasons. First, there exists a strong heterogeneity in B2B customers (e.g., size of the firm, industry) which affect demand. Therefore, in many B2B exchanges, order customization is prevalent (e.g., compare the customized lithography machines of ASML in the high-tech industry to standard clothing sales of Zara in fast fashion). Second, B2B channels are more complex than B2C channels due to the critical personal channel. The salespeople have valuable tacit knowledge about customers thanks to their personal interactions, which makes them indispensable. These unique challenges of learning about customers in B2B will thus be at the core of this PhD project.

This PhD project aims to provide a broader view on the application of AI to learn from customers than to merely find the optimal algorithm to do so. First, an important consideration in this project is the role of "explainable AI." As the outcomes should support both the operational planners, the potential benefits of AI learning will only materialize if planners understand and trust these outcomes. Second, AI learning will unveil customer preferences, and these might not merely be operationally-driven. As Homburg et al. (2013) point out, supplier-customer relationships can also be (indirectly) strengthened via corporate social responsibility efforts that include stakeholders outside the firm's business operations.

4.3 Research methodology (e.g., research procedure, research design, models, sample, measures, statistics)

Within this project, we distinguish two types of learning about the customer, which we expect to be complementary: learning about customers *from customers*, and learning about customers *from employees*.

Learning about customers from customers
We will draw on recent developments in statistical learning (Hastie, Tibshirani & Friedman, 2009) and causal inference (Angrist and Pischke, 2008). Statistical learning techniques are suited to work with high-dimensional data, e.g. including many supplier-customer interactions and customer characteristics, yet these techniques have the drawback that they are not necessarily suited to deal with common endogeneity problems. Therefore, we will also build on causal inference techniques, answering to recent calls for more empirical causal inference research in the field of operations (e.g. Ho et al. 2017, Ketokivi & McIntosh 2017 and Lu et al. 2018) to learn from customers.

Learning about customers from employees
The forecasting literature has repeatedly shown that knowledge of planners can be captured by building models based on past planner behavior using a technique known as judgemental bootstrapping (see e.g., Arvan et al. 2019). While the primary interest in this project is not on forecasting, insights from the judgmental bootstrapping literature will be used to build models that capture the knowledge of planners and salespeople and help them make better operational decisions in serving customers. For a recent example on pricing decision, see Karlinsky-Shichor and Netzer (2021).

4.4 Relevant literature for the project, with separate citation of relevant literature of the research group and data sources

References

Angrist & Pischke (2008) Mostly harmless econometrics: An empiricist's companion. Princeton University Press.

Arvan, Fahimnia, Reisi & Siemsen (2019) Integrating human judgement into quantitative forecasting methods: A review. Omega, 86, 237-252.

Bastani, Harsha, Perakis & Singhvi (2018) Sequential learning of product recommendations with customer disengagement. Working paper. MIT .

Calmon, Ciocan & Romero (2021) Revenue management with repeated customer interactions. Management Science, forthcoming.

Chen, Owen, Pixton & Simchi-Levi (2021) A statistical learning approach to personalization in revenue management. Management Science, forthcoming.

DHL (2021) The Ultimate B2B E-commerce Guide: Tradition is out. Digital is in. Whitepaper

Ho, Lim, Reza & Xia (2017) OM forum—Causal inference models in operations management. Manufacturing & Service Operations Management, 19(4), 509-525.

Ketokivi & McIntosh (2017) Addressing the endogeneity dilemma in operations management research: Theoretical, empirical, and pragmatic considerations. Journal of Operations Management, 52, 1-14.

Lu, Ding, Peng & Chuang (2018) Addressing endogeneity in operations management research: Recent developments, common problems, and directions for future research. Journal of Operations Management.

Martínez-de-Albéniz, Planas & Nasini (2020) Using clickstream data to improve flash sales effectiveness. Production and Operations Management, 29(11), 2508-2531.

Hastie, Tibshirani & Friedman (2009) The elements of statistical learning: data mining, inference, and prediction. Springer Science & Business Media.

Homburg, Stierl & Bornemann (2013) Corporate social responsibility in business-to-business markets: How organizational customers account for supplier corporate social responsibility engagement. Journal of Marketing, 77(6), 54-72.

Karlinsky-Shichor & Netzer (2021) Automating the B2B salesperson pricing decisions: Can machines replace humans and when? Available at SSRN 3368402.
Sawhney & Piper (2002) Value creation through enriched marketing–operations interfaces: an empirical study in the printed circuit board industry. Journal of Operations Management, 20(3), 259-272.
Ulaga & Eggert (2006) Value-based differentiation in business relationships: Gaining and sustaining key supplier status. Journal of Marketing, 70(1), 119-136.

Relevant literature of the research group

The team has a strong track record in the area of marketing-operations interface. The most important papers in this domain are listed below:

Gelper, S., Wilms, I., & Croux, C. (2016). Identifying demand effects in a large network of product categories. Journal of Retailing, 92(1), 25-39.
Khooban, Mutlu, Gelper & de Kok (2021) Country-wide logistics capability and cross-border demand in e-commerce: The moderating role of institutions. Working paper. Eindhoven University of Technology.
Langerak (2001) Effects of market orientation on the behaviors of salespersons and purchasers, channel relationships, and performance of manufacturers. International Journal of Research in Marketing, 18(3), 221-234.
Li, Konuş, Pauwels, & Langerak (2015) The hare and the tortoise: do earlier adopters of online channels purchase more? Journal of Retailing, 91(2), 289-308.
Mutlu & Bish (2019) Optimal demand shaping for a dual-channel retailer under growing e-commerce adoption. IISE Transactions 51.1, 92-106.
Torkaman, Akbari Jokar, Mutlu & Van Woensel (2020) Solving a production routing problem with price-dependent demand using an outer approximation method. Computers & Operations Research, 123, 105019.

The team also has a strong methodological track record:

Alfons, Croux & Gelper (2016) Robust Groupwise Least Angle Regression, Computational Statistics & Data Analysis – Special Issue on Advances in Data Mining and Robust Statistics, 93, 421-435.
Alfons, Croux & Gelper (2013) Sparse Least Trimmed Squares Regression for Analyzing High-Dimensional Large Data Sets, Annals of Applied Statistics, 7, 226-248.
Gelper, Fried & Croux, C. (2010) Robust Forecasting with Exponential and Holt-Winters Smoothing, Journal of Forecasting, 29, 285-300.
Gelper, Schettlinger, Croux & Gather (2009) Robust Online Scale Estimation in Time Series: A Model-Free Approach, Journal of Statistical Planning and Inference, 139, 335-349.

5. Relevance

5.1 For the European Supply Chain Forum

We will work together with ESCF companies interested in building long-term customer relationships through AI enabled learning and, of course, in contributing to scientific work. The team is currently already working intensely together with Hilti for both PhD and Master thesis research. We plan to broaden the set of companies to manufacturing companies and IT solution providers from the Data2Move community. The research will be shared with the ESCF full members and community members during the events, and by writing content for the website. As this research has a strong customer focus, it is particularly relevant for the "Customer Sensing and Responding" charter in the Data2Move community (Sarah), and for the Customer-Driven Transformations community (Nevin).

5.2 For the IE&IS department

The marketing-operations interface topic of the project fits directly with the departmental theme "Logistics and Interfaces." The project further strengthens the ongoing collaboration between ITEM and OPAC, and contributes to the valorisation strategy by delivering value to industry.

5.3 For EAISI

A classic business application of AI is the recommender system – which learns about customers. A recommender system infers customer preferences to be able to intelligently suggest additional products that the customer is interested in. In this project, we take a much more ambitious approach to learning about customers. Specifically, we will not just learn which products the customer is interested in, but we will learn how to best serve the customer in the long-term. In addition to the algorithmic challenges, we will take into account aspects related to explainable AI and corporate social responsibility, thus contributing to the "Human-centered AI" theme within EAISI.

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

1. Title of the PhD project

Context matters: optimizing shared decision making in real-world forecasting and inventory management

2. Brief summary of the main research issue (max. 200 words)

In many organizations and across industries, artificial intelligence (AI) is transforming the way we work. AI-systems are implemented to assist employees with decision making, to decrease workload, or to increase efficiency. Although promising, transforming traditional operations into ones that rely on autonomous systems brings many challenges. For example, when using AI planning systems, users frequently experience difficulties in using and trusting these systems and, as a consequence, deviate from their advice. Prior research highlights the impact of system characteristics (e.g. reliability) on human-AI collaboration. However, these studies disregard the important **influence of contextual factors on human-AI collaboration**. Therefore, one important challenge concerns the consideration of contextual factors when **designing and implementing AI-systems at work**. To successfully integrate these systems in organizational processes, it is critical to understand when and why users are (un)willing to adopt these systems in their work routines and how we can stimulate effective usage. The goal of this PhD-project is to address these issues by answering the following research questions: (1) Which contextual factors, specifically organizational (e.g. organizational climate, leadership) and societal factors (e.g. COVID-19 pandemic), impact planners' willingness to use AI planning systems? (2) How can human-centered AI and work design help to improve human-AI collaboration?

3. Composition of the research group

Name, title(s)	Role (promotor/ (daily) supervisor/	Discipline	To the account of	Hours / week
Prof. dr. P. Le Blanc	promotor	Workplace Innovation and Sustainable Employability	HPM Group	1
Dr. P. van de Calseyde	daily supervisor	Decision Making	HPM Group	2
Dr. A.S. Ulfert	daily supervisor	Organizational Behavior and AI	HPM Group	2

4. Description of the project (1-2 pages)

4.1 Specification of the main research problem (i.e., key research problems and research aims)

Olsen and Tomlin (2020) indicate that complementing human strengths with novel technologies is one of the key promises of the Industry 4.0 revolution. Future decision making processes will in many cases be a combination of human judgement and algorithms (Fahimnia et al., 2019; Tetlock & Gardner, 2016). This means that, even with continuous development of system capabilities, future AI-planning systems will still require a certain degree of human involvement to guarantee quality and safety standards. Better quality of inventory planning and forecasting is related to higher profitability and a higher quality customer service, making planning systems highly attractive. Human planners can further add value to the planning and forecasting systems as they can identify the events that are unforeseen by the system and integrate these into the advice they obtain from the statistical algorithms (van der Staak, 2021). Therefore, a significant number of companies uses some combination of a human planner and a planning system. Evaluating the performance and efficiency of the decisions that planners make in relation to the advice they obtain from the planning system, is an essential component in these operational processes. In order to make the best use of these planning systems, it is essential to understand the determinants of successful collaboration between human planners and planning systems.

One of the HPM group's prior research projects, reported in the recent dissertation of Bregje van der Staak, analyzes how, when, and why planners adjust the advice provided by a planning system. This project explored the role of individual (round number preferences, biases, crafting) and work design factors (task complexity) impacting planners' collaboration with planning systems. Although the focus was on individual level factors, it was suggested that planners' reasons for adjusting a system's prediction is depending on the (organizational) context too. Therefore, context factors, as for example leadership, organizational or team climate, shared team mental models, or disruptive societal events like the current COVID-19 pandemic, may strongly impact this collaboration in complex real life scenarios.

Literature in the field of human-computer interaction (HCI) further supports this assumption and postulates that depending on individual or contextual factors, collaboration effectiveness can strongly differ between users, systems, and organizations. Theories such as the Technology Acceptance Model (e.g. TAM 3, Venkatesh & Bala, 2008) offer first insights into human-AI collaboration and aim to predict acceptance and adoption of technological innovations by individual users. Though insightful, only recently, these theories have highlighted the potential role of contextual factors (Venkatesh et al., 2016). Additionally, most of these suggested relationships are yet to be empirically tested. This is problematic, particularly as – according to organizational change literature - contextual factors play a key role in successful transitions (see Hayes, 2018, for an overview). Similarly, contextual factors have been suggested as important predictors of trust in automation (Schaefer et al., 2016).

In the presented project, we want to focus on decision making processes when collaborating with AI-planning systems. Specifically, we aim to highlight different perspectives on these decision making processes from an individual, team, organizational, and societal level. Furthermore, we will investigate how context factors impact both AI-assisted decision making processes and perceptions of these decisions within the organization (e.g., perception of employee agency). Results of the proposed project will (1) help to build improved models of human-AI interaction to be considered when designing human-centered AI systems and (2) develop strategies for successfully implementing and effectively using planning systems within organizations.

4.2 Scientific importance and relevance of the project (i.e., innovative aspects, embedding in literature, added value)

Organizational research highlights the importance of adopting a multilevel perspective when studying real-world phenomena in organizational contexts (Costa et al., 2013; Kozlowski & Klein, 2000). In contrast, HCI research thus far predominantly focusses on studying the bilateral interaction between a single user and a system. We argue that in order to develop better systems and to foster effective human-AI collaboration, we will need to investigate AI-assisted decision making processes from a multilevel perspective. Extensions of classic HCI theories, such as the TAM and theories of trust in technology, address this multilevel perspective by adding societal and contextual factors (Schaefer et al., 2016; Venkatesh et al., 2016). Systematic studies of the effects of these factors on technology acceptance and trust are however still lacking. The suggested project adds to current research by applying a multilevel perspective to AI-assisted decision making processes when using planning systems, considering effects of contextual factors on effective collaboration between the system and human users.

4.3 Research methodology (e.g., research procedure, research design, models, sample, measures, statistics)

The proposed project will consist of the following four phases:

1. **Analysis:** In a first step, multi-disciplinary literature on collaboration with AI-systems, planning systems, human-AI teaming, automated decision making, technology use in organizations, leadership, technology acceptance, and trust in technology will be reviewed, analyzing the role of contextual factors. Results of the literature review will help to build an initial framework, identifying core contextual factors (organizational and societal). In a second step, we will analyze when, why, and how planners use (and/or misuse) AI-decision support systems in organizations. The analysis will investigate organizational factors such as organizational climate or leadership and their impact on planners' decision making processes. Using qualitative (critical incident technique) and quantitative (surveys) studies, we will investigate these questions with users of AI-planning systems in the industry (in collaboration with ESCF partners). Results will be used to derive a preliminary model of contextual factors and conditions impacting AI-collaboration in planners' decision making processes.
2. **Behavioral experiments** with students and professionals will be conducted to systematically test facilitating factors identified in phase 1. In a first step, different user scenarios of

collaborations between planners and planning systems will be developed and tested. In a second step, these scenarios will be used to simulate collaboration under different contextual conditions (e.g. routine vs. erroneous situation; high vs. low leadership support). Results will be used to validate and refine the proposed model.

3. **Develop design approaches** for work and system design in order to improve collaboration by increasing usability, user acceptance, and trust in these systems. The proposed model will be used to derive guidelines for (1) implementing AI-planning systems within organizations and (2) building improved user models that will help to improve operational processes when introducing planning systems into organizations and may be integrated into future systems.

4.4 Relevant literature for the project, with separate citation of relevant literature of the research group and data sources

Relevant publications of the research group:

Efendic, E., Van de Calseyde, P. P. F. M., & Evans, A.M. (2020). Slow response times undermine trust in algorithmic (but not human) predictions. *Organizational Behavior and Human Decision Processes, 157,* 103–114.

Le Blanc, P.M., Gonzalez-Romá, V. & Wang, H.J. (2020). Charismatic leadership and work team innovative behavior: the role of team task interdependence and team potency. *Journal of Business and Psychology, 36*, 333-346.

Ton, B., Basten, R., Bolte, J., Braaksma, J., Di Bucchianico, A., Van De Calseyde, P.P. F. M., … Stoelinga, M. (2020). PrimaVera: Synergising predictive maintenance. *Applied Sciences, 10* (23), 8348.

Ulfert, A. S., & Georganta, E. (2020). A Model of Team Trust in Human-Agent Teams. *Proceedings of the 2020 International Conference on Multimodal Interaction, 1*, 171-176.

Van de Calseyde, P.P.F.M., Evans, A.M., & Demerouti, E. (in press). Leader decision speed as a signal of honesty. *The Leadership Quarterly.*

Van der Staak, B. (2021). *Adjust or accept suggestions by algorithms. Uncovering human behavior in forecasting and inventory planning* [Unpublished doctoral dissertation]. Eindhoven University of Technology

Relevant literature:

Costa, P. L., Graça, A. M., Marques-Quinteiro, P., Santos, C. M., Caetano, A., & Passos, A. M. (2013). Multilevel research in the field of organizational behavior: An empirical look at 10 years of theory and research. *Sage Open*, *3*(3), 2158244013498244.

Fahimnia, B., Pournader, M., Siemsen, E., Bendoly, E., & Wang, C. (2019). Behavioral operations and supply chain management–a review and literature mapping. *Decision Sciences*, *50*(6), 1127–1183.

Hayes, J. (2018). *The theory and practice of change management*. Palgrave.

Kozlowski, S. W. J., & Klein, K. J. (2000). *A multilevel approach to theory and research in organizations: Contextual, temporal, and emergent processes.*

Olsen, T. L., & Tomlin, B. (2020). Industry 4.0: Opportunities and challenges for operations management. *Manufacturing & Service Operations Management*, *22*(1), 113–122.

Schaefer, K. E., Chen, J. Y. C., Szalma, J. L., & Hancock, P. A. (2016). A Meta-Analysis of Factors Influencing the Development of Trust in Automation: Implications for Understanding Autonomy in Future Systems. *Human Factors*, *58*(3), 377–400. https://doi.org/10.1177/0018720816634228

Tetlock, P. E., & Gardner, D. (2016). *Superforecasting: The art and science of prediction*. Random House.

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. *Decision Sciences*, *39*(2), 273–315.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, *17*(5), 328–376.

5. Relevance

5.1 For the European Supply Chain Forum

The proposed project is a multidisciplinary approach to developing and implementing future AI-planning systems. Planning systems are already used in the context of operations and supply chain management. With their superior capabilities in detecting patterns and events and deriving appropriate actions, many organizations strive to implement AI-systems into their work processes. Although the use of these advanced systems has rapidly progressed in recent years, employees still regularly experience difficulties in their initial adoption and continued use. To get at the core of understanding facilitating factors when implementing AI-planning systems in organizations, this research project will provide three major insights relevant to the ESCF partners: understanding individual and contextual factors (organizational and societal) that impact AI-collaboration to be considered in (1) system design, (2) work design and (3) implementation. With an increased demand for developing and implementing AI-systems in organizations, these insights will become central to the ESCF partners' operations.

5.2 For the IE&IS department

Within the IE&IS department, our research project relates to the central research theme of Humans and Technology, which the department defined as both scientifically challenging and societally relevant. Moreover, it is of relevance for the research theme on Logistics and its interfaces too. It extends prior research projects by the HPM/OPAC groups and therefore strengthens the department's expertise on the topic of human-AI collaboration. Extending the department's research portfolio in this future oriented research field touches on many up to date and highly relevant challenges. Due to its relevance to both research and industry, this will path a way for many future collaborations.

5.3 For EAISI

The proposed research agenda fits the goals and focus of EAISI in multiple ways. First, set in the context of autonomous machine operations and smart human-operator support, the project aims at understanding human-AI collaboration in dynamic and complex real-world settings. This new approach to human-AI interaction research offers to extend current insights in this field by including contextual and societal factors as major influences on human-AI collaboration. Second, the project is situated within EAISI's key domain 2 (Humans and human-centered AI) and its key research challenges. With a strong focus on the AI as a partner rather than a tool, the proposal supports the assumption that research has to rethink the relationship that exists between AI and the human user. To develop this new type of relationship, research and development will be required regarding the design of the AI-systems as well as the design of organizations and jobs. Only by approaching human-AI collaboration from a multilevel and multidisciplinary perspective, we can benefit from both the AI's and the human operator's competences. To reach this goal, it is necessary to gain a deeper understanding of this relationship in real-world contexts, as it is proposed in this project.

1. Title of the PhD project

AI-Based Replenishment and Order Fulfillment Strategies for Omnichannel Supply Chains

2. Brief summary of the main research issue (max. 200 words)

While retailers are investing heavily in integrating online channels to their traditional offline channels, only a few giant players' efforts are profitable. The main problem is the failure to integrate essential operations of online and offline channels. To tackle this problem, this PhD research provides a real-time, data-driven AI-based planning strategy by integrating the decisions on three cornerstones of omnichannel retail: 1) inventory replenishment policy, 2) customer fulfilment policy, and 3) consumer delivery options and prices. We provide a new AI-based methodology to enable the real-time integrated control of these three cornerstones. Our study provides the omnichannel retailers with decision support tools that tell them when and where products in the supply chain should be replenished and stored and how customer orders should be fulfilled. In this way, we identify profitable omnichannel business models that will help these business to stay alive in the e-commerce market.

3. Composition of the research group

Name, title(s)	Role (promotor/ (daily) supervisor/	Discipline	To the account of	Hours / week
Dr. Zumbul Atan	Co-promoter	SCM		3
Dr. Albert H. Schrotenboer	Co-promoter	AI and Transportation		3
Prof. Tom van Woensel	Promotor	Retail and Transportation		2

4. Description of the project (1-2 pages)

4.1 Specification of the main research problem (i.e., key research problems and research aims)

The ecommerce market is sky-rocketing from \$2.3 trillion in sales in 2017 to an expected \$4.5 trillion by the end of 2021 [1]. To serve the online consumers and stay competitive with giant global players such as Amazon, the traditional offline retailer has become an omnichannel retailer; it offers online sales next to offline, in-store sales.

While many retailers focus on the rapidly growing ecommerce revenue, the truth is that ecommerce profits have been far from elusive due to the complexity of providing the customer-centric online operations. Except a few global giant players, all retailers report that online channels are draining their overall profits. Even then, they keep operating these channels hoping to remain competitive and gain market shares. The fundamental question that is how to address the profit woes of online channels. Practical evidence in combination with the scientific literature provides valuable hints on the problem's source; the failure to integrate essential operations of online and offline channels. To best-satisfy customers' preferences and control costs, products should move flexibly and quickly through the supply chain, requiring a *new, data-driven, real-time planning* mindset at the omnichannel retailers.

This PhD research aims to provide this real-time, data-driven planning by integrating the three cornerstones of omnichannel retail: 1) inventory replenishment decisions, 2) customer fulfilment decisions, and 3) consumer delivery options and prices. We provide a *new AI-based methodology* to enable the real-time integrated control of these three cornerstones. That is, when and where products in the supply chain should be replenished and stored (e.g., at local stores, distribution centres, or city hubs), and how customer orders should be fulfilled (e.g., from which channel, what transportation modes, what service-promise, which price). In this way, we identify profitable omnichannel business models that will help these businesses to stay alive in the e-commerce market.

To this end, we consider a general omnichannel setting with multiple physical stores and distribution centers, and study the real-time planning within. Surprisingly, there does not exist literature that considers such an integrated joint planning of product replenishment and order fulfilment. Moreover, the literature does also fail to address the link between fulfilment and replenishment on the one hand, and consumer service promises and its associated pricing on the other hand.

To address the above-identified omnichannel planning problems, we will build upon AI-based planning methods that propose real-time decisions that anticipate upon future uncertainty and actions. We envision that the PhD research entails the following four research projects:

1. Given a store replenishment strategy, study order fulfilment policies based on dynamic rationing and lateral transhipments to minimize system-wide operating cost.
2. Given consumer delivery options, study the joint optimization of store replenishment and order fulfilment policies to further minimize the system-wide operating cost and its impact on network design requirements.
3. For high-potential omnichannel networks (indicated in projects 1 and 2) we study the benefits and operational costs of offering multiple online delivery alternatives (fast and expensive vs. regular and cheap deliveries) and optimize the delivery specifications, i.e., lead time and prices (delivery specification policy).
4. Study the added value of each optimal policy, i.e., *optimal fulfillment policy, optimal replenishment policy and optimal delivery specification policy* to provide recommendations and practical insights.

4.2 Scientific importance and relevance of the project (i.e., innovative aspects, embedding in literature, added-value)

This PhD research contributes to three streams of Operations Research Literature. These are 1) rationing for multiple customer classes, 2) emergency lateral transhipments among multiple locations and 3) omnichannel retailing operations. It further contributes in general to the application of AI for stochastic, sequential decision making in Operations Research.

In online retailing, customers could be categorized by their delivery time requests. Some customers may pay a higher fee for shorter delivery times. Although the retailers eventually fulfil all their orders, the optimal fulfilment strategy might require reserving part of the inventory for customers who demand fast deliveries (critical level policy). In addition, stores might employ rationing policies to discriminate among online and offline demands. There are multiple studies on static critical level policies [2, 3] but in an online retailing setting, where inventory levels across locations change dynamically, a dynamic critical level policy would perform better. This PhD research considers dynamic critical level policies with multiple customer types (online-fast delivery, online-regular delivery and offline). These policies are not studied in the literature before, and will be addressed in Project 1.

When a store prefers not to satisfy a non-urgent online demand (for the sake of reserving inventory for orders with fast delivery requests or offline customers), another store in the network might be asked to satisfy the demand [4, 5, 6]. As long as the demand is satisfied, it makes no difference to the customer which store satisfies the demand. The order fulfillment decision is closely linked to this transhipment problem, as sharing inventory is made easily possible in an online retailing environment. The benefits and associated costs of dynamic transhipment policies in an omnichannel settings are not studied in the literature before, and will be addressed in Projects 1 and 2.

Although there are studies that look at the static fulfillment decisions at the order level, the opportunity lies in jointly and dynamically optimizing the fulfillment decisions along the inventory replenishment and delivery specification decisions [7, 8, 9]. This PhD research aims at developing models to jointly optimize these three policy decisions and contributing to the understanding of onmichannel retailers on where to concentrate their efforts by analyzing the marginal effect of each optimal policy. All omnichannel retails will benefit from our results, recommendations and insights, as we aim to show in Projects 3 and 4.

To address these research gaps, we build upon recent advances in Deep Reinforcement Learning (DRL). High-potential is observed in amongst others, inventory control problems [10, 11, 12] and last-mile delivery pricing and routing [13]. This PhD research will build upon these recent successful applications of AI, and in specific DRL. This PhD research aims to show the applicability of AI for OR problems that are assumed to be unsolvable with traditional optimization techniques.

4.3 Research methodology (e.g., research procedure, research design, models, sample, measures, statistics)

The research methodology is grounded in the unified framework for stochastic optimization [14]. Using MDP theory, this PhD research will start with designing a unified model of omnichannel fulfilment, replenishment, and delivery options and pricing. To deal with the combinatorial explosion of states an actions, this research will build upon recent successful application of combining offline simulation with DRL to find solutions to MDPs. We will also leverage supervised learning principles, to find a mapping of system characteristics to system performance. We will explore Approximate Dynamic Programming approaches such as cost-function approximations to learn the non-trivial total system costs as a function of the action space [15]. Finally, this research aims to combine the new AI-driven methods with existing optimization techniques to incorporate domain knowledge [16]. Our methods will be compared with traditional optimization techniques, myopic policies, and decomposition approaches.

4.4 Relevant literature for the project, with separate citation of relevant literature of the research group and data sources

[1] Goodson, J. 2020. "Is 2020 the year that made Omnichannel retail's new normal?" https://www.detego.com/retail_insights_en/retail-en/omnichannel_retail_2020/.

[2] **Atan, Z.**, Snyder, L. V. & Wilson, G.R. (2018). "Transshipment policies for systems with multiple retailers and two demand classes." OR Spectrum, 40(1), 159-186.

[3] Mahdavi, M. & Olsen, T.L. (2021). "The duel-serving problem: What is the right choice of inventory strategy?" OMEGA, forthcoming.

[4] Acimovic, J. & Gaves, S.C. (2015). "Making Better Fulfillment Decisions on the Fly in an Online Retail Environment." Manufacturing & Service Operations Management, 17(1), 34-51.

[5] Yang, J. & Qin, Z. (2007). "Capacitated production control with virtual lateral transshipments." Operations Research, 55(6), 1104-1119.

[6] Poormoaied, S., **Atan, Z.,** de Kok, T. & **van Woensel, T.** (2020). "Optimal Inventory and Timing Decisions for Emergency Shipments." IISE Transactions, 52(8), 904-925.

[7] Bretthauer, K., Mahar, S. & Venakataramanan, M. (2010). "Inventory and distribution strategies for retail/e-tail organizations". Computers & Industrial Engineering, 58(1), 119-132.

[8] Poormoaied, S., **Atan, Z.** & **van Woensel, T.** (2021). "Pricing and Delivery Lead Time Policies for Online Retailers." Working paper. Eindhoven University of Technology.

[9] Ahmadi, T., **Atan, Z**., de Kok, T & Adan, I. (2019). "Optimal Control Policies for an Inventory System with Committment Lead Time", Naval Research Logistics, 66(3), 193-212.

[10] Gijsbrechts, J., Boute, R. N., Van Mieghem, J. A., & Zhang, D. (2018). Can deep reinforcement learning improve inventory management? Performance and implementation of dual sourcing-mode problems. Performance and Implementation of Dual Sourcing-Mode Problems (December 17, 2018).

[11] Van Jaarsveld, W. (2020). Model-based controlled learning of MDP policies with an application to lost-sales inventory control. arXiv preprint arXiv:2011.15122.

[12] Oroojlooyjadid, A., Nazari, M., Snyder, L. V., & Takáč, M. (2021). A Deep Q-Network for the Beer Game: Deep Reinforcement Learning for Inventory Optimization. M&SOM, forthcoming.

[13] Ulmer, M. W. (2020). Dynamic pricing and routing for same-day delivery. Transportation Science, 54(4), 1016-1033.

[14] Powell, W. B. (2019). A unified framework for stochastic optimization. European Journal of Operational Research, 275(3), 795-821.

[15] **Schrotenboer A. H.,** Uit het Broek, M. A. J., Buijs, P. & Ulmer, M. W. (2021). "Efficient routing policies for instant delivery platforms". Working paper. Eindhoven University of Technology.

[16] Sonntag, D. R., **Schrotenboer, A. H.** & Kiesmüller, G. P. (2021). "Tactical Stochastic Inventory Routing". Preprint available at http://www.optimization-online.org/DB_FILE/2020/11/8094.pdf.

5. Relevance

5.1 For the European Supply Chain Forum

The project is relevant to all ESCF companies that already operate online/onmi-channels (for example VidaXL, Nike, Jumbo, Bonduelle). In addition, it provides useful recommendations and insights for (potential member) companies that consider introducing online channels. Given that we rely on AI-based solution methodology, the project also contributes to ESCF's vision on having AI as one of the core ESCF topics. The application of AI in the described specific setting is new and we plan to organize workshops to inform our members on our findings. We also aim to perform pilot implementations at the interested member companies.

5.2 For the IE&IS department

This PhD research is aligned with the IE&IS Department's ambition of developing data-driven AI-based methods for solving new, challenging and important real-world problems. Hence, it contributes the department's efforts of integrating the methodological AI-based innovations into Operations Management problems. The proposed topic constitutes one of the moonshots of the department's Logistics& Interfaces Research Theme's short-term roadmap. Hence, it is relevant to the department's aim of conducting cutting edge research on practical problems with huge societal relevance.

5.3 For EAISI

Given that we rely on AI-based solution methodology, this PhD research is quite relevant to EAISI as the institute aims to bring all AL activities of TU/e together. The project contributes to the Next-Gen Industry moonshot of EAISI as we aim to empower the onmichannel retailers to become more economically and environmentally sustainable. It also contributes to the Trustworthy Data moonshot as the pilot implementations with ESCF companies requires creating algorithms for anonymization of consumer and company data.

1. Title of the PhD project

Robust data-driven sustainable food supply chain

2. Brief summary of the main research issue (max. 200 words)

Food supply chains contain different types of uncertainty; from quality of supplied material to traffic congestion in last-mile delivery. These uncertainties often result in food losses and waste, aggravating the environmental footprint of the chain. As such, there is a need for robust policies that can address this uncertainty. Recently, we have seen how machine learning techniques, such as Neural or Kernel-based classifications, are used in Robust Optimization to derive robust policies by extracting important information from historical data. However, the computational complexity of these approaches still remains an issue. In this project, we want to build on this recent stream of research and design approaches in data-driven robust optimization capable of tackling problems arising in food supply chain settings. By using machine learning techniques within the framework of robust optimization we intend to then design robust policies that mitigate the negative effects of uncertainties within the food system.

3. Composition of the research group

Name, title(s)	Role (promotor/ (daily) supervisor/	Discipline	To the account of	Hours / week
Tom van Woensel	Promotor	Logistics	TU/e OPAC	1
Ahmadreza Marandi	Daily supervisor	Robust Optimization	TU/e OPAC	4
Sonja Rohmer	Co-supervisor	Logistics/ Food supply chains	TU/e OPAC	4

4. Description of the project (1-2 pages)

The food system is a highly complex and dynamic (global) network involving multiple agents, a large product variety, and many types of processes. A generic food supply chain may, for example, consist of farmers producing agricultural crops or livestock, processing facilities where production of intermediary and final products takes place, specialised warehouses to store products, logistic providers who transport the products to customers or retailers, and retailers who sells the final products to the customers (see Figure 1). Each step in this chain may furthermore have specific requirements with regards to cold chain technology and handling of products to ensure food safety and prevent product decay.

Globalisation and differences in the underlying social and ecological systems, such as climatic and geographical conditions or the development status of a country, affect the transparency and complicate sustainable decision making in the food system. Adding to the inherent complexity in the system, uncertainty brings another layer of complexity to the decision-making process. Actors in the food system operate in a highly uncertain environment, facing

Figure 1: Schematic overview of agents involved in a food supply chain

uncertainty in the supply of specific raw materials as well as the demand of specific products, uncertainty in quality (freshness) of the raw materials and products, and uncertainty in travel times due to traffic conditions when distributing products, just to list a few.

Therefore, it is of great importance to consider the presence of uncertainty while designing a sustainable food system. Rohmer et al. (2019) show that for a class of products significant improvements can be obtained to move toward sustainable systems. However, it is still unclear how the system would look like when considering different classes of uncertainties.

In this project, we aim to develop a robust data-driven approach to design a sustainable food system. As the design decisions are rather tactical (Rohmer et al. (2019), Coelho and Laporte (2014), Li et al. (2018), and Li et al. (2020)), the historical data on the realization of the uncertain parameters may not provide us with exact forecasts for the future. Therefore, using good techniques to develop robust decisions is crucial. Robust Optimization (RO) is such a technique, which tries to find robust decisions that are safe guarded against future uncertainties.

Recently, machine learning (ML) approaches such as deep learning (DL) and kernel-based classifications (KC) have been used to extract information from historical data for RO formulations (Goerigk and Kurtz (2020), Ning and You (2018), Garuba et al. (2020), and Shang et al. (2017)). Despite a good quality solution, the combination of ML approaches and RO poses some computational challenges. In this project, we aim to deploy such combinations in food systems with different sources of uncertainty.

4.1 Specification of the main research problem (i.e., key research problems and research aims)

In this project, we consider a production-inventory-routing (PIR) problem in the presence of supply, demand, and traffic uncertainty. There are three main classes of decisions in PIR problems, namely decision on supply quantity, production and inventory, and shipments. Figure 2 provides the schematic overview of how events occur in a PIR problem.

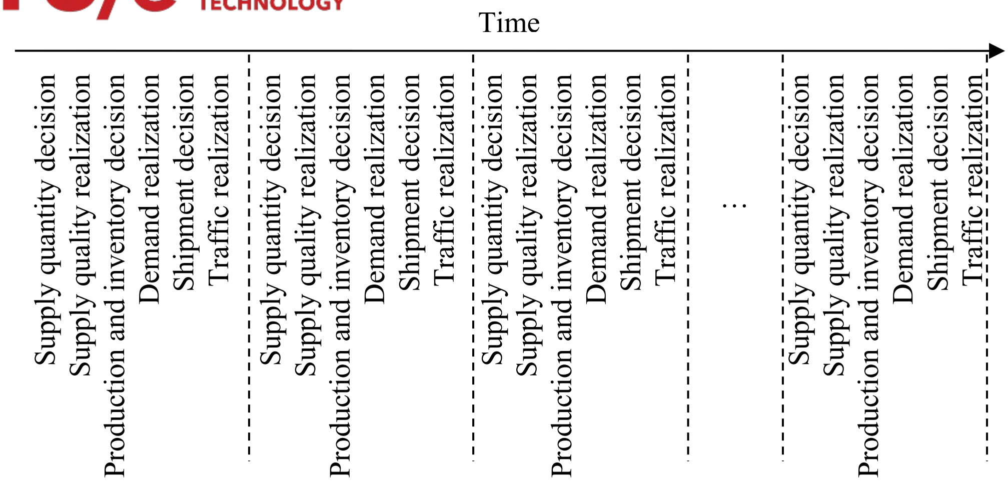

Figure 2 Schematic overview of the events

As one can see in Figure 2, all decisions in the PIR problem are affected by the uncertainty in quality of supply, quantity of demand, and traffic conditions. Considering the time horizon, we see that the decisions are made sequentially multiple times, creating a multi-stage environment.

In this project, we aim to answer the following questions:

RQ1. How to combine ML approaches, like DL and KC, with RO in the two-stage inventory-routing problem of perishable products?

In the start of the project, we only focus on the small version of the problem, namely the inventory-routing problem (Alvarez et al., 2020), where the decisions are on the inventory policy and shipment policy with uncertainty of demand and traffic conditions (Figure 3). Considering the available historical data on the demand and traffic, we investigate how to use ML approaches to extract the needed information for the two-stage RO formulation. Then, we develop numerical methods to solve the formulated problem.

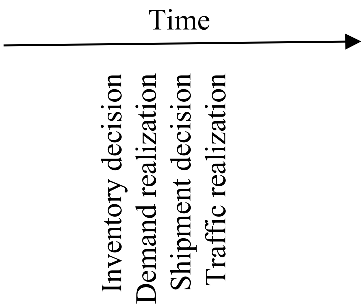

Figure 3 Schematic overview of the events in two-stage inventory-routing problem

RQ2. How to extend the results of RQ1 to a two-stage production-inventory-routing problem of perishable products?

In this part of the project, we aim to extend the results of RQ1 by involving the uncertainty on the quality of the supplied materials and the production decisions (Figure 4). The combination of perishability and involvement of all decisions and uncertain parameters results in a highly computationally complex model (Belo-Filho et al., 2015). Therefore, we investigate how we can extend the results in RQ1 to be able to deal with the two-stage PIR problem.

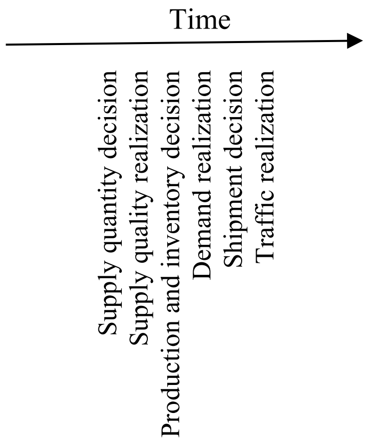

Figure 4 Schematic overview of the events in two-stage production-inventory-routing problem.

RQ3. How to extend the results to a multi-stage production-inventory-routing of perishable products?

In the last phase of the project, we consider the multi-stage PIR problem. Extending the results from two-stage to multi-stage is not straightforward as the dependence of decisions to the future uncertainty increases when we go from two- to multi-stage. Furthermore, the use of ML approaches in multi-stage environments provides more computational complexity. The main reason is the dynamic nature of multi-stage environment, where the uncertain parameters are realized multiple times and the model should be able to understand how to update the extracted information from the ML approaches when new batches of data arrive. Therefore, in this part of the project, we first analyze how the dynamic nature of the problem can be captured in an ML approach and then use it to formulate RO.

4.2 Scientific importance and relevance of the project (i.e., innovative aspects, embedding in literature, added-value)

We are living in a world full of data. But the question of how to use such available data in future decision making remains an open challenge. In this project, we aim to develop a novel data-driven methodology for a class of food supply chains. With the use of our approaches, we have a more disciplined way of using historical data in decision making process and increase the transparency.

In our method, we use ML approaches to extract necessary information used in RO formulation. The combination of ML approaches and RO has been recently used in toy examples. In this project, we aim to mature the use of ML approaches for RO in PIR problems.

4.3 Research methodology (e.g., research procedure, research design, models, sample, measures, statistics)

In this project, we mainly focus on the combination of ML approaches and Robust Optimization techniques. From the ML perspective, we mainly focus on DL and KC. The recent investigation shows that DL extracts more accurate information from historical data than KC and results in a better solution for a shortest path problem (Goerigk and Kurtz 2020). However, KC can better capture the dynamic of multi-stage problems but is more computationally challenging.

As the combination of DL or KC with RO results in a nonlinear optimization problem, we develop nonlinear optimization approaches to solve the two-stage problems formulated from the use of DL or KC in PIR problems. Based on the results of this part of the project, we then investigate which ML approach can better capture the dynamic nature of multi-stage settings while staying manageable in terms of computational complexity.

4.4 *Relevant literature for the project, with separate citation of relevant literature of the research group and data sources*

References

Alvarez, A., Cordeau, J. F., Jans, R., Munari, P., & Morabito, R. (2020) Formulations, branch-and-cut and a hybrid heuristic algorithm for an inventory routing problem with perishable products. *European Journal of Operational Research* 283 (2): 511-529.

Belo-Filho, M. A. F., Amorim, P., & Almada-Lobo, B. (2015) An adaptive large neighbourhood search for the operational integrated production and distribution problem of perishable products. *International Journal of Production Research* 53 (20): 6040-6058.

Coelho, L. C., & Laporte, G. (2014) Optimal joint replenishment, delivery and inventory management policies for perishable products. *Computers & Operations Research* 47: 42-52.

Garuba, F., Goerigk, M., & Jacko, P. (2020) A comparison of data-driven uncertainty sets for robust network design. *arXiv preprint arXiv:2003.10507.*

Goerigk, M., & Kurtz, J. (2020) Data-Driven Robust Optimization using Unsupervised Deep Learning. *arXiv preprint arXiv:2011.09769.*

Li, Y., Chu, F., Côté, J. F., Coelho, L. C., & Chu, C. (2020) The multi-plant perishable food production routing with packaging consideration. *International Journal of Production Economics* 221: 107427.

Li, Y., Chu, F., Feng, C., Chu, C., & Zhou, M. (2018) Integrated production inventory routing planning for intelligent food logistics systems. *IEEE Transactions on Intelligent Transportation Systems* 20 (3): 867-878.

Ning, C., & You, F. (2018) Data-driven decision making under uncertainty integrating robust optimization with principal component analysis and kernel smoothing methods. *Computers & Chemical Engineering* 112: 190-210.

Rohmer, S. U. K., Claassen, G. D. H., & Laporte, G. (2019) A two-echelon inventory routing problem for perishable products. *Computers & Operations Research* 107: 156-172.

Rohmer, S. U. K., Gerdessen, J. C., & Claassen, G. D. H. (2019) Sustainable supply chain design in the food system with dietary considerations: A multi-objective analysis. *European Journal of Operational Research* 273 (3): 1149-1164.

Shang, C., Huang, X., & You, F. (2017) Data-driven robust optimization based on kernel learning. *Computers & Chemical Engineering* 106: 464-479.

Relevant literature of research group:

Torkaman, S., Jokar, M. R. A., Mutlu, N., & **Van Woensel, T.** (2020). Solving a production-routing problem with price-dependent demand using an outer approximation method. *Computers & Operations Research*, *123*, 105019.

Crama, Y., Rezaei, M., Savelsbergh, M., & **Van Woensel, T.** (2018). Stochastic inventory routing for perishable products. *Transportation Science*, *52*(3), 526-546.

Ehrenthal, J. C. F., Honhon, D., & **Van Woensel, T.** (2014). Demand seasonality in retail inventory management. *European Journal of Operational Research*, *238*(2), 527-539.

Marandi, A., & van Houtum, G. J. (2020). Robust location-transportation problems with integer-valued demand. *Optimization Online*.

Roy, A., Dabadghao, S. S., & **Marandi, A.** (2020). Towards Adaptive Robust Radiotherapy to Manage Radioresistance. *Annals of Operations Research*.

Marandi, A., & Den Hertog, D. (2018). When are static and adjustable robust optimization problems with constraint-wise uncertainty equivalent?. *Mathematical programming*, *170*(2), 555-568.

Rohmer, S. U. K., Claassen, G. D. H., & Laporte, G. (2019). A two-echelon inventory routing problem for perishable products. *Computers & Operations Research*, *107*, 156-172.

Rohmer, S. U. K., Gerdessen, J. C., & Claassen, G. D. H., 2019. Sustainable supply chain design in the food system with dietary considerations: A multi-objective analysis. *European Journal of Operational Research,* 273(3), pp. 1149-1164.

Chevroton, H., **Rohmer, S. U. K.**, & Billaut, J. C. (2021). A production and distribution framework: Manufacturer dominates. *Computers & Industrial Engineering*, *155*, 107162.

5. Relevance

5.1 For the European Supply Chain Forum

European Supply Chain Forum (ESCF) has the goal of enabling the professionals in and around supply chains to create, exchange, and integrate knowledge by collectively exploring the future. We know that the traditional decision-making process will be obsolete and replaced with data-driven decision making. In this project, we aim to develop a data-driven decision-making method around production-inventory-routing problems, which can be beneficial for the full members of ESCF as well as the members of data-2-move and customer-driven transformation communities.

5.2 For the IE&IS department

Production-inventory-routing problems form an important class of Operations Management problems. By developing a data-driven decision-making method, we will take the next step in moving toward the next generation of supply chains. Hence, with this work, the IE&IS department becomes among the leading research institutions where data-driven decision-making methods will be developed.

5.3 For EAISI

We contribute to the two EAISI missions: "**Decision making under uncertainty in complex engineering systems**", "**Merging model-driven and data-driven approaches as a basis for learning**". We will use and complement learning methods to extract necessary information from data to be used in RO. Then, we develop computationally efficient approaches to obtain robust policies that are safe guarded against future uncertainties.

1. Title of the PhD project

Digital Twins: An ingenious AI companion or an evil twin?

2. Brief summary of the main research issue (max. 200 words)

Digital twinning and remote visualization technologies rapidly gain popularity for the design and maintenance of (complex) production systems. Digital twinning is not a new term but paired with advancements in artificial intelligence (AI) and augmented reality (AR), it is increasingly valuable in transforming industrial operations, which, in turn, leads to the creation of additional business value. Digital twinning involves embedding sensors in Internet-of-Things-connected, complex industrial machines and applying artificial intelligence and machine-learning algorithms to the resultant big data. A sophisticated visualization of the machine allows remote engineers to proactively optimize productivity, reduce maintenance cost, and extend product life cycles. Although proactive actions make the manufacturer seem "closer" to the customer's business than ever before, paradoxically, the remote elements in digital twinning limit real-life customer contact that is needed to build loyal customer relationships and to gather ideas for new and improved products.

Hence, while digital twinning can be an ingenious companion in optimizing operational decisions, it may also act as an evil twin that hampers marketing and innovation outcomes. Manufacturers need a solution for this pressing issue, but current literature has not yet considered the potential dark side of digital twinning in an interdisciplinary manner.

3. Composition of the research group

Name, title(s)	Role (promotor/ (daily) supervisor/	Discipline	To the account of	Hours / week
Néomie Raassens, dr.	Co-promotor	Servitization		4
Jeroen Schepers, dr.	Co-promotor	Frontline Service and Innovation		4
Tom van Woensel, prof.dr.	Promotor	Freight Transport & Logistics		2

4. Description of the project (1-2 pages)

4.1 Specification of the main research problem (i.e., key research problems and research aims)

The main research question of this PhD research is: How can manufacturers optimize the operations, marketing, and innovation outcomes of digital twinning collectively?

To address this main question, we aim for an integrative solution at three levels.

First, at the operational level, the main question is how firms should balance and manage digital and real-life interactions with customers. Previous literature has developed mathematical models that support firms in making decisions to optimize costs and machine uptimes, but marketing and innovation outcomes have so far been neglected.

Second, at the business level, the main question is how AI-driven technologies such as digital twins and AR can facilitate cooperation between research and development (R&D), marketing, and (field) service. AI provides both new opportunities for enhanced cooperation between departments (e.g., smartly scheduling new product demos with maintenance activities) but also offers challenges (e.g., potentially limiting grassroots innovation from the service domain).

Third, at the employee level, the main question is how digital twins, AI, and AR can improve employee decisions. Although literature stresses the value of digital twinning and AI for better decisions in a controlled production environment, the value of these advancements remains unclear in customer-focused environments. In fact, service engineers may feel monitored or outsmarted by the technology; the challenge is to reach optimal decisions through collaborative intelligence, i.e., artificial and human intelligence.

4.2 Scientific importance and relevance of the project (i.e., innovative aspects, embedding in literature, added-value)

Today, the big data-driven manufacturing era is coming (Tao et al. 2018, 2019). Many manufacturers were already focused on digital transformations pre-pandemic, before COVID-19 accelerated the pace of building digital capabilities across the globe (McKinsey & Company 2020). Connected devices and systems will radically change the nature of manufacturing (Shih and Ludwig 2016).

Because of the rapid development of virtual data and data acquisition technologies, digital twin technology is increasingly applied in manufacturing industries (Lu et al. 2020; Wang et al. 2021). A digital twin enables the integration of data between a physical and virtual machine (Wu et al. 2021). Because of current market conditions, i.e., high uncertainty and low growth, manufacturers are forced to squeeze every asset for maximum value (McKinsey & Company 2017). This is reflected in academic research, in which the focus is on how firms could use digital twins to optimize productivity, reduce maintenance cost, and extend product life cycles.

To date, few efforts have been devoted to exploring how the application of the digital twin technology affects marketing and innovation outcomes. While literature acknowledges the potential of using digital twins, involving the use of AI, AR, and big data, to align firms' product and service offerings to customer demand, empirical validation of this presumption is lacking. It could even be argued that, through the use of digital twins, virtual interactivity and connectivity with customers is overstated and physical interactions and connections with customers undermined. In a similar vein, academic literature shows that digital twins are able to support the (innovative) product design process (e.g., Tao et al. 2019). However, while technically the potential of digital twinning to support innovation processes is present, far less guidance is available on how firms should leverage this potential.

To conclude, while manufacturers generate enormous volumes of data and have jumped on the AI bandwagon, many have failed to leverage its potential (McKinsey & Company 2017), especially regarding marketing and innovation. An integrative approach is called for, in which operational, marketing, and innovation outcomes are central and in which both the positive as well as the possible dark sides of digital twin technology is investigated.

4.3 Research methodology (e.g., research procedure, research design, models, sample, measures, statistics)

The PhD project will be executed in close collaboration with ESCF members. In individual talks with the members of the servitization community, the members indicate that new technological advancements, such as digital twinning, AI, and AR, are important in transitioning their business models in order to stay competitive. In this PhD project, we aim for close collaboration with these members, and use their operational and performance data as input for the intended studies. To complement these data, we would like to gather survey data. Collected data serve as input to mathematical models and multivariate statistical analyses.

4.4 Relevant literature for the project, with separate citation of relevant literature of the research group and data sources

References:

Lu, Y., C. Liu, K.I.-K. Wang, H. Huang, and X. Xu (2020), "Digital Twin-Driven Smart Manufacturing: Connotation, Reference Model, Applications and Research Issues," *Robotics and Computer Integrated Manufacturing*, 61, 101837.

McKinsey & Company (2017), "Manufacturing: Analytics Unleashes Productivity and Profitability," available at https://www.mckinsey.com/business-functions/operations/our-insights/manufacturing-analytics-unleashes-productivity-and-profitability.

McKinsey & Company (2020), *The Next Normal: The Recovery Will Be Digital*, McKinsey Global Publishing: 1-172.

Shih, W.C., and H. Ludwig (2016), "The Biggest Challenges of Data-Driven Manufacturing," *Harvard Business Review*, available at https://hbr.org/2016/05/the-biggest-challenges-of-data-driven-manufacturing.

Tao, F., J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui (2018), "Digital Twin-Driven Product Design, Manufacturing and Service with Big Data," *The International Journal of Advanced Manufacturing Technology*, 94, 3563-3576.

Tao, F., F. Sui, A. Liu, Q. Qi, M. Zhang, B. Song, Z. Guo, S. C.-Y. Lu, and A.Y.C. Nee (2019), "Digital Twin-Driven Product Design Framework," *International Journal of Production Research*, 57 (12), 3935-3953.

Wang, X., Y. Wang, F. Tao, and A. Liu (2021), "New Paradigm of Data-Driven Smart Customisation through Digital Twin," *Journal of Manufacturing Systems*, 58, 270-280.

Wu, C., Y. Zhou, M.V.P. Pessôa, Q. Peng, and R. Tan (2021), "Conceptual Digital Twin Modeling Based on an Integrated Five-Dimensional Framework and TRIZ Function Model," *Journal of Manufacturing Systems*, 58, 79-93.

Relevant literature from the research group:

Belanche, D., Casaló, L.V., Flavián, C. and **Schepers, J.** (2020), "Robots or Frontline Employees? Exploring Customers' Attributions of Responsibility and Stability after Service Failure or Success," *Journal of Service Management*, 31 (2), 267-289.

Belanche, D., Casaló, L.V., Flavián, C. and **Schepers, J.** (2021), "Service Robot Implementation: A Theoretical Framework and Research Agenda," *The Service Industries Journal*, 40 (3-4), 203-225.

Hrusovsky M., E. Demir, W. Jammernegg, and T. **Van Woensel** (2020), "Real-Time Disruption Management Approach for Intermodal Freight Transportation," *Journal of Cleaner Production*, 280, 124826.

Raassens, N., S. Wuyts, and I. Geyskens (2012), "The Market Valuation of Outsourcing New Product Development," *Journal of Marketing Research*, 49 (5), 682-695.

Raassens, N., S. Wuyts, and I. Geyskens (2021), "Is Outsourcing Eroding Firms' Innovativeness?" *working paper*.

Schepers, J.J.L., E.J. Nijssen, and G.A.H. Van der Heijden (2016), "Innovation in the Frontline: Exploring the Relationship between Role Conflict, Ideas for Improvement, and Employee Service Performance," *International Journal of Research in Marketing*, 33 (4), 797-817.

Vos, M.A., N. **Raassens**, M. van der Borgh, and E.J. Nijssen (2018), "Balancing Modularity and Solution Space Freedom: Effects on Organizational Learning and Sustainable Innovation," *International Journal of Production Research*, 56 (20), 6658-6677.

5. Relevance

5.1 For the European Supply Chain Forum

The PhD project will be embedded in the servitization community of the European Supply Chain Forum (ESCF). Members of this community are shifting from a product-centric business model and logic to a service-centric approach. Firms are doing so in an attempt to capture additional value from services, partly to counterbalance ever-quicker commoditization that threatens their product offerings and erodes their market position. Additionally, customers are increasingly demanding solutions that integrate products with services. Digital twinning, AI, and AR are important tools in this regard. However, while firms recognize the potential of these technological advancements, they face some worrisome challenges to use them to their advantage. Our aim is to closely collaborate with these members, organize ESCF events to disseminate the gained knowledge, and create public content by means of the ESCF website and Link Magazine. The main objective is to make academic insights available to the broader public by solving real-life problems with scientific rigor.

5.2 For the IE&IS department

The Department of Industrial Engineering & Innovation Sciences (IE&IS) is engaged in strategic-technological research and aims for both scientific excellence and societal relevance. To this end, the Department IE&IS has identified four cross-disciplinary research themes: (i) logistics and its interfaces, (ii) sustainability, (iii) value of big data, and (iv) humans and technology.
This PhD project contributes especially to the research themes 'logistics and its interfaces' and 'value of big data'. By taking an interdisciplinary perspective, in particular by integrating operations management, strategic marketing management, and innovation management, this PhD project integrates different research domains to assist companies to stay competitive in the digital era. Additionally, by focusing on digital twinning, AI, and AR as major technological advancements, this PhD project aims to guide firms in translating big data in useful information to make their business stronger (i.e., more productive, more customer centric, more innovative).

5.3 For EAISI

The Eindhoven AI Systems Institute (EAISI) brings together all AI activities of the TU/e. By investigating how manufacturers can optimize operations, marketing, and innovation outcomes by digital twinning, this PhD project could be connected to the moonshot 'nextgen industry', in which AI and engineering disciplines are merged. Collaboration could be sought with the Digital Twin Lab of EAISI. Moreover, because the PhD project can be classified as application driven research, this PhD project fits with EAISI's aim to stimulate and increase collaborations with industry partners and to create an impact on the real world.

1. Title of the PhD project

AI for sustainable last-mile delivery by micromobility: a socio-technical perspective

2. Brief summary of the main research issue (max. 200 words)

This project aims to understand the opportunities and context of using AI for last-mile delivery by micromobility, contributing to innovating sustainable urban logistics and reducing carbon emissions. A particular focus will be on active micromobility such as cargo-ebikes.

3. Composition of the research group

Name, title(s)	Role (promotor/ (daily) supervisor/	Discipline	To the account of	Hours / week
Frauke Behrendt	First and daily supervisor	TIS		
Floor Alkemade	First Promoter	TIS		

4. Description of the project (1-2 pages)

4.1 Specification of the main research problem (i.e., key research problems and research aims)

Last-mile logistics have a significant carbon footprint, driven up, among others, by the increase in online shopping and associated delivery vans. Micromobility can make a major difference to reducing carbon emissions and congestion around last-mile delivery, as proven by several recent studies. Micromobility is a very dynamic niche, and cargo e-bike are becoming particularly relevant for urban logistics, with a range of startups [e.g. ONO], emerging industry networks (e.g. ECLF), and EU projects [e.g. ULaaDs], and increasing uptake by the industry (e.g. DHL). The International Transport Forum defines micromobility as vehicles weighing up to 35 or 350 kg (depending on type) and whose power supply (if any) is gradually reduced and cut off at a given speed limit, no higher than 25 or 45 km/h (depending on type); and this includes exclusively or partially human-powered vehicles such as bicycles and cargo e-bikes. The project will contribute to understanding how the niche of micromobility can grow to change the current regime of last-mile logistics.

While AI approaches are increasingly used in logistics and supply chains, they are almost entirely focused on traditional vans and trucks. Contemporary logistics innovations around micromobility such as e-cargo bikes involve new ICT solutions, novel vehicles, experiments with urban microhubs – but hardly any engagement with AI. This project would bring both perspectives and innovations together. It would also consider the inclusion of harder to measure concepts such as sustainability into the planning process. The complexities associated with the emergence of distributed and mobile microhubs in cities could be one key area to benefit from AI planning. The importance of AI for logistics is increasing. Leaving micromobility out of these important developments would marginalize it, instead of contributing to further uptake.

The project takes a socio-technical perspective that considers data, algorithms, vehicles, riders, freight, policies, regulations, business models, the urban environment, etc, to understand the potential synergies between the innovations of AI and micromobility, but also to critically interrogate their claims around sustainability. It does so in the context of broader societal developments such as datafication, algorithmic society, online shopping, urbanization and climate change. A recent review observes that "there has been relative silence on how to explore the specific context of AI for environmental sustainability" and calls for a "focus on the non-technical: people, processes, and policy aspects of information systems", and identifies transportation as key domain for this (Nishant *et al.* 2020, p. 2). This project would contribute to these debates on AI for sustainability from a transport and socio-technical perspective.

The research objectives are to:

- Conceptualize AI-micromobility as socio-technical system
- Chart the emerging use of AI for micromobility in the Netherlands and the EU (startups, projects, pilots, innovations)
- Map relevant Dutch stakeholders, procedures and frameworks (industry, policy, users) that are relevant for AI use of micromobility logistics
- Identify what kind of data is and is not collected in the industry around micromobility, and how this informs or prevents AI approaches (e.g. training data for ML), also compared to how other transport modes of AI-driven logistics
- Understand the benefits and potential downsides of AI-use for micromobility in terms of sustainability (considering both the mobility and the IT side, e.g. energy use)
- Create industry and policy recommendations for the use of AI in the context of micromobility

4.2 Scientific importance and relevance of the project (i.e., innovative aspects, embedding in literature, added-value)

See above. Will be indicated in more detail for the next draft.

4.3 Research methodology (e.g., research procedure, research design, models, sample, measures, statistics)

Methods include technology analysis, case studies, expert interviews, policy reviews and stakeholder mapping. In addition to academic outputs, the project will also contribute industry and policy recommendations for the role of AI for sustainable urban micromobility logistics.

4.4 Relevant literature for the project, with separate citation of relevant literature of the research group and data sources

Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. International Journal of Information *Management*, *53*(April), 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104

OECD/ITF. (2020). *Safe Micromobility*. https://www.itf-oecd.org/safe-micromobility

Rieck, F. (n.d.). *Urban Technology Research Programme City Logistics : Light and Electric*.

Relevant literature by the research group/supervisor team (Behrendt: B1-3; Alkemade: A1-3):

[B1] Kiefer C, Behrendt F (2015) Smart E-Bike Monitoring System: realtime open-source and open hardware GPS, assistance and sensor data for electrically-assisted bicycles. Journal IET Intelligent Transport Systems: 1-10. https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/iet-its.2014.0251

[B2] Behrendt F (2019) Cycling the Smart and Sustainable City: Analyzing EC Policy documents on Internet of Things, Mobility and Transport, and Smart Cities. Sustainability. 11(3): 1-30. https://www.mdpi.com/2071-1050/11/3/763

[B3] Behrendt F (2016) Why Cycling Matters for Smart Cities. Internet of Bicycles for Intelligent Transport. Journal of Transport Geography. 56: 156–64. https://www.sciencedirect.com/science/article/abs/pii/S0966692316300746

[A1] van der Kam, M., Peters, A., van Sark, W. G. J. H. M., & Alkemade, F. (2019). Agent-based modelling of charging behaviour of electric vehicle drivers. Journal of Artificial Societies and Social Simulation, 22(4), [7]. https://doi.org/10.18564/jasss.4133

[A2] Köhler, J., Geels, F. W., Kern, F., Markard, J., Wieczorek, A., Alkemade, F., et al (2019). An agenda for sustainability transitions research: state of the art and future directions. Environmental Innovation and Societal Transitions, 31, 1-32. https://doi.org/10.1016/j.eist.2019.01.004

[A3] Persoon, P. G. J., Bekkers, R. N. A., & Alkemade, F. (2020). The science base of renewables. Technological Forecasting and Social Change, 158, [120121]. https://doi.org/10.1016/j.techfore.2020.120121

5. Relevance

5.1 For the European Supply Chain Forum

Potential ESCF members as project partners: DHL, Jumbo or MediaMarktSaturn, MediaDPg.

5.2 For the IE&IS department

AI Planner of the future projects this could relate to: 'AI-based Optimization using Digital Twins for Sustainable Last-Mile Delivery' (Zhang, Bliek) where micromobility could be one of the modes considered; also, projects share the concern with sustainable last-mile delivery

5.3 For EAISI

This project mainly contributes to the EAISI application area Mobility. It clearly addresses the moonshot 'zero accident and zero emission mobility'. The project will also contribute to Democratizing AI, as as it will apply AI to a domain that is under-served in terms of AI approaches: micromobility.

1. Title of the PhD project

Data-driven Optimization using Digital Twins for Sustainable Last-Mile Delivery

2. Brief summary of the main research issue (max. 200 words)

Due to the complexity of modern supply chains, it is difficult to predict what the effect will be of a decision aimed at reducing greenhouse gas emissions, such as choosing the location of a pick-up point, or changing the travel route for a vehicle. Digital twins make it possible to try these decisions in a virtual environment before applying them in real life. This helps policy-makers in governments and companies gain a better understanding of the consequences of a decision, which reduces the risks and uncertainties of the radical new decisions that are necessary to achieve the sustainable supply chain of the future.

With the rise of digital twins for smart cities, such as the Atlas Livable City developed by the Logistics Community Brabant, more data is readily available than ever before. Yet most existing optimization techniques, which are necessary for minimizing an objective such as travel time or greenhouse gas emissions, are not able to deal with such complex virtual environments. Data-driven optimization techniques are therefore an active area of research. Examples of this are optimization heuristics learned with machine learning, and surrogate models for optimization. This project will contribute to this active research landscape by making data-driven optimization techniques that are suitable for digital twins. The main application is the reduction of greenhouse gas emissions in last-mile delivery by choosing the locations of pick-up points in urban environments.

3. Composition of the research group

Name, title(s)	Role (promotor/ (daily) supervisor/	Discipline	To the account of	Hours / week
Yingqian Zhang	Promotor	AI/ML	IS	1
Laurens Bliek	Daily Supervisor / Copromotor	AI/ML	IS	2
Tom van Woensel	2nd Promotor	Logistics, mobility	OPAC	0.25

4. Description of the project (1-2 pages)

4.1 Specification of the main research problem (i.e., key research problems and research aims)

This project has two main topics that are closely connected: digital twins for sustainable last-mile delivery, and data-driven optimization for digital twins.

Digital twins for sustainable last-mile delivery

Digital twins are a key component of the Smart City movement, where logistic operations through-out a city are improved using data. The Atlas Livable City [10,11] is an example of such a digital twin that is already being used by local governments and companies to gain more insight into logistical policies. As the data is focused on mobility for urban environments, this tool provides an excellent opportunity for making more informed decisions concerning last-mile delivery for multi-stakeholders, such as governmental policies on low emission zones and parking regulations, decisions concerning distribution modes (home deliveries, collection points, etc), transportation modes (vehicles, e-cargo-bikes, drones) and hub placement, or operational decisions such as routing.

Besides gaining insights, a digital twin can also be used to make predictions of the effect of certain policies, or even to search for optimal policies with respect to a cost function such as fuel consumption or greenhouse gas emissions. This project focuses on policies related to *hub placement* in last-mile delivery: what are the optimal locations of pickup-points for urban delivery. While large vehicles such as trucks are used for delivering goods to a pickup-point, smaller vehicles such as urban e-trucks, e-cargo-bikes, drones or robots can be used for the last-mile delivery from pickup-point to customer. The mode of transportation is also seen as a policy in this project, and it is closely related to hub placement as the optimal locations might depend on the transportation mode.

Traditional optimization methods are not adequate for finding the optimal policy for this problem for several reasons: 1) optimal routes for the urban vehicles need to be computed every time a new hub location is evaluated, 2) the digital twin is too complex to be described by mathematical equations but does contain a large amount of data, and 3) urban environments are full of uncertainties. Because of these complexities, we turn to *data-driven* solutions.

Data-driven optimization for digital twins

Modern optimization techniques are often combined with data-driven techniques such as machine learning in order to deal with the complexities of real-life optimization problems. Examples of these data-driven optimization techniques are learning heuristics [1,5], surrogate models [3,7,8,9], learning unknown constraints [4], or using optimization for machine learning [6]. When looking for optimal decisions inside a digital twin, using data-driven optimization techniques is a must. Especially surrogate models are considered to be a suitable method for digital twins due to their low computational demands and their ability to deal with both data and first principles [2]. This project will investigate how data-driven optimization techniques such as surrogate models can be used in digital twins for sustainable last-mile delivery.

Research goals

The main outcome of this project is a data-driven optimization method that is closely intertwined with a digital twin, and that provides policies that are optimal with respect to a well-defined sustainability measure. To achieve this, various aspects need to be investigated:

1. Define a sustainability measure that corresponds to real-life objectives for last-mile delivery, while also being easy to learn and to optimize for the data-driven optimization methods.
2. Adapt data-driven optimization methods to make them suitable for digital twins.
3. Make use of the digital twin's relation to its physical twin (the real world) to *close the loop*: use data-driven optimization to suggest optimal decisions for the real world, but also use feedback from the real world system to learn and improve.
4. Quantify the uncertainty that arises due to the mismatch between real world and digital twin, or due to unexpected events in the real world.
5. Combine first principles knowledge with data present in the digital twin.

Collaborations

We plan to collaborate with Logistics Community Brabant, who has been developing the Atlas Livable City, and with ESCF members such as DHL, ORTEC, Jumbo, and others who are interested in data-driven solutions for sustainable last-mile delivery. The policies that come out of this project can be used not only by the collaborating partners but also by other "AI planner of the future" projects such as "AI for sustainable last-mile delivery by micromobility: a socio-technical perspective" (Frauke Behrendt). In turn that project is beneficial for this project by investigating the data, stakeholders and existing solutions.

4.2 Scientific importance and relevance of the project (i.e., innovative aspects, embedding in literature, added-value)

Data-driven optimization is an active research field, but very little has been done for digital twin applications. This research would link the three important research areas of machine learning, optimization and digital twins together, rather than looking at each aspect separately from the rest. While both data-based solutions and digital twins are actively researched for last-mile delivery and other urban logistical problems, the combination of these, and especially the combination with optimization methods, is an innovative one that has a lot of potential. There is also a large potential societal impact in achieving sustainable last-mile delivery for different stakeholders: replacing large trucks with small electric vehicles in urban environments and optimizing operations can reduce greenhouse gas emissions, alleviate traffic congestion, improve health, shorten delivery times, and reduce cost.

4.3 Research methodology (e.g., research procedure, research design, models, sample, measures, statistics)

The research in this project will contain methodologies present in data science as well as in optimization, such as data understanding and algorithm design. Choices regarding the machine learning models and optimization techniques used will be made based largely on the data. The designed methodologies will be compared with naïve solutions, such as random decisions or local search techniques which are not data-driven, as well as with oracle solutions that have access to "future" data that is otherwise considered unknown.

4.4 Relevant literature for the project, with separate citation of relevant literature of the research group and data sources

[1] Bengio, Y., Lodi, A., & Prouvost, A. "Machine Learning for Combinatorial Optimization: a Methodological Tour d'Horizon." Eur. J. Oper. Res. 290 (2021): 405-421.

[2] Bárkányi, Á, Chován, T, Németh, S, & Abonyi, J. Modelling for Digital Twins—Potential Role of Surrogate Models. Processes. 2021; 9(3):476.

Literature of the research group

[3] Bliek, L., Verwer, S., & de Weerdt, M. Black-box Combinatorial Optimization using Models with Integer-valued Minima. Ann Math Artif Intell (2020).

[4] Verwer, S., Zhang, Y., & Ye Q.C. Auction optimization using regression trees and linear models as integer programs. Artificial Intelligence. Volume 244, pages 368–395, 2017

[5] de O. da Costa, P.R., Rhuggenaath, J., Zhang, Y., & Akcay, A. Learning 2-opt Heuristics for the Traveling Salesman Problem via Deep Reinforcement Learning. in Proceedings of The 12th Asian Conference on Machine Learning. Proceedings of Machine Learning Research, vol. 129, PMLR, pp. 465-480, 2020.

[6] Verwer, S., & Zhang, Y. Learning optimal classification trees using a binary linear program formulation. In 33rd AAAI Conference on Artificial Intelligence, AAAI 2019

[7] Rijnen, D. J. F., Rhuggenaath, J., Costa, P. R. D. O. D., & Zhang, Y. (2019). Machine learning based simulation optimisation for trailer management. In 2019 IEEE International Conference on Systems, Man and Cybernetics, SMC 2019 (pp. 3687-3692)

[8] Bliek, L., Verstraete, H.R.G.W., Verhaegen, M., & Wahls, S. Online Optimization With Costly and Noisy Measurements Using Random Fourier Expansions. IEEE Transactions on Neural Networks and Learning Systems 29 (2018): 167-182.

[9] Karlsson, R., Bliek, L., Verwer, S., & de Weerdt, M. Continuous surrogate-based optimization algorithms are well-suited for expensive discrete problems. BNAIC/BENELEARN (2020), pages 88-102.

Data sources

[10] https://www.lcb.nu/nieuws/details/?id=dd315361-d01d-eb11-a813-000d3abac0b9

[11] https://atlasleefbarestad.digitwin.app

5. Relevance
5.1 For the European Supply Chain Forum

Several ESCF members are working with last-mile delivery. How to do this in a sustainable way is on the agenda for several of these members. Finding optimal decisions for solving this problem, while first trying them without any risk in a virtual environment, will take away a lot of the risk for these industrial partners, while also yielding better solutions than with a purely descriptive approach.

Sustainability is also a key aspect of the description “AI planner of the future”: *“it is also important to investigate (if and) how AI enables supply chains and logistics to make a major contribution towards reducing greenhouse gas emissions (Dauvergne 2020)”*.

While sustainability is a hard to measure concept, this project will make it more concrete as the measure needs to be implemented in machine learning and optimization algorithms.

Furthermore, the data-driven optimization methods developed in this project can be used in other supply chain applications with digital twins.

5.2 For the IE&IS department

The project fits three research themes of IE&IS: Value of big data, logistics and its interfaces, and sustainability. This research will benefit from close collaboration of expertises of different research groups: AI and machine learning based decision support (IS), optimization for urban logistics (OPAC), and socio-technical study in sustainability (TIS).
Within the “AI planner of the future” program, it is connected closely to the project “AI for sustainable last-mile delivery by micromobility: a socio-technical perspective” (Frauke Behrendt).

5.3 For EAISI

Mobility is a key application area of EAISI, and responsible mobility is one of its moonshots. This project will speed up the transition to zero emission mobility, which is one of the goals of EAISI.

This project is also closely connected to several research themes within EAISI, for example:

- Democratizing Artificial Intelligence, by making use of digital twins to immediately see the effect of optimal policies.
- Merging Models and Data in AI, by merging first-principles approaches with data-driven approaches and learning system behaviour.
- Certifiable, Robust, and Explainable AI, by learning and dealing with uncertainty in the system.

1. Title of the PhD project

Online Supply Chain Planning

2. Brief summary of the main research issue (max. 200 words)

Supply chain planning is complex because of complex dependencies of the delivery of the final product on the timely shipping, assembly, production, and procurement of its parts. Periodic supply chain plans are made. However, during the execution of the plan, it must often be adapted, for example, because parts are delivered late or because production is delayed. This leads to changes to the plan that are often ad-hoc and suboptimal, and cause planning 'nervousness', i.e. frequent planning changes. Consequently, in addition to periodic planning, supply chain planning can benefit from planning techniques that assist with the day-to-day adaptations of the supply chain plan, due to the unexpected situations that arise. These 'online' planning techniques must take the current periodic plan into account, as well as the current status of the procurement, production, and assembly of the parts. It should then advise on changes to the plan, while minimizing planning nervousness and costs. In this project we aim to develop such a technique for online supply chain planning, using novel techniques from the area of artificial intelligence that can learn to predict – based on the current situation and unexpected events that must be handled – what the best solution is to plan for the unexpected event. A general framework for these techniques is being developed in a related project, where applications in production and transportation planning are studied. The aim of this project is to make this general framework suitable for supply chain planning. Against this background, the project has a specific focus on encoding and learning the complex relations and patterns of dependency between different activities in supply chain planning, which to the best of our knowledge has not been studied before.

3. Composition of the research group

Name, title(s)	Role (promotor/ (daily) supervisor/	Discipline	To the account of	Hours / week
Remco Dijkman	First promotor	Information Systems		1
Willem van Jaarsveld	Second promotor/ daily supervisor	Operations Planning Accounting and Control		2

4. Description of the project (1-2 pages)

4.1 Specification of the main research problem (i.e., key research problems and research aims)

During the execution of a supply chain planning, various things can go wrong. For example, parts can be delivered late or be of insufficient quality, production can be delayed, and customers may shift their demand forward or backward. When this happens the supply chain planning must be adjusted to take such an unexpected event into account. However, current supply chain planning systems are not well suited to support with adjusting supply chain plans. Consequently, shifting one order – the one for which there is a problem – leads to shifts in other orders as well. This creates 'planning nervousness' and is undesirable, because it leads to stress in the own organization as well as customer and supplier dissatisfaction. In addition to that the changes to the plan may be suboptimal from a cost perspective.

To help solve these problems, we aim to create algorithms that are specifically tailored to support replanning of orders due to unexpected events as they occur. These algorithms must minimize both planning nervousness and supply costs. The algorithms must focus on the online aspects of the planning problem. Specifically, the problems that must be solved are the following.

1. The problem of handling unexpected events in supply chain planning must be modelled in such a way that an online algorithm - specifically a Deep Reinforcement Learning (DRL) Algorithm - can be used to solve it.
2. The DRL algorithm must be improved by investigating ways to include real-time information as well as predictions about the current state of the supply process.
3. To make the algorithm more efficient, a specific solution approach based on process similarity must be investigated, where situations are compared to each other based on their similarity to each other – as well as successful solution from the past – in order to quickly find viable solutions.

4.2 Scientific importance and relevance of the project (i.e., innovative aspects, embedding in literature, added-value)

Driven by the recent success of DRL in playing complex board games, there is a strong drive to research the possibilities of DRL in solving real-world planning problems. There already is ample evidence that DRL can play an important role in efficiently solving real-world planning problems that must be solved in (near) real-time, use real-time data, or have a strong stochastic element.

Some examples of this potential include the following. Previous research by the same group showed that using DRL to take batching decisions in warehouse management led to a reduction of the number of tardy orders by 3.7% (Cals, Zhang, Dijkman, van Dorst, 2021). We have also shown that DRL can be successfully used to solve train shunting problems, where DRL finds better and more consistent plans than current heuristics (Peer, Menkovski, Zhang, Lee, 2018). Other research, which studied assigning rides to customers at a ride-hailing company, showed that using a DRL-based solution led to a 0.5-2% increase in the number of orders that could be fulfilled, while using the same number of resources (Qin et al., 2020). Each of these problems had a strong uncertain element in their arrivals (of picking orders, trains, or ride requests) and were able to plan based on real-time data about the current state of resources and orders.

While there exist general solution techniques and frameworks to create DRL solutions (Bargiacchi, Roijers, Nowé, 2020; Brockman et al., 2016; Plappert, 2016; Castro et al., 2018), these frameworks aim at solving general DRL problems, including the complex board games mentioned before. There is a real need to develop a similar framework specifically targeted at solving planning problems. We envision zero-code (or low-code) ways for modelling and solving planning problems and have shown the convenience of such solutions (Van Jaarsveld, 2020).

Specifically, this project aims to contribute to existing efforts that are going on in the research group to develop a framework for using DRL to solve planning problems using zero-code or low-code. It extends this work by developing modelling techniques that can specifically be used to model supply chain planning problems, including their mappings to a Markov Decision Process (MDP) that can be solved using DRL, and a comparison of the best algorithmic chains (Neural Network Architectures, Solver Algorithms, and First-stage Bootstrap Learners) to solve those problems. While doing so, there will be a specific focus on modelling and learning the dependencies between different supply chain planning problems, which is essential in supply chain planning, and not currently covered in the ongoing work.

4.3 Research methodology (e.g., research procedure, research design, models, sample, measures, statistics)

The research will be done by solving concrete supply chain planning problems at ESCF partners. In a joint roadmap, ESCF partners Ampleon, Nexperia, NXP, Hilti and Philips have indicated that they are interested in exploring the use of DRL for solving their supply chain planning problems. AMS and Neways have indicated that they are interested in exploring solutions for integrated supply chain planning problems, while not explicitly mentioning DRL as a direction. In this project, we aim to work on concrete problems at least for three of these partners, using their processes and data as case studies to drive the research.

We envision three research studies that are in line with the three main research problems as they are identified in section 4.1.

In the first study, MDP models will be made of the supply problems of the industry partners, where the state transitions also represent the unexpected events that must be considered in the supply chain plans. DRL will be used as the main technique for optimizing the MDP. The results of the DRL optimization will be compared to a benchmark method of periodically solving a constraint programming problem. These solutions will be compared to the current practice in terms of total supply costs and planning nervousness.

In the second study, prediction models will be made to predict the occurrence of unexpected events. Different modelling techniques will be attempted and a literature study will be used to look for the most promising modelling techniques. Two promising directions at least include predicting the transition probabilities in the MDP depending on current values of the MDP state, for example, using decision trees, such as proposed by Gumuskaya et al. (2020). Another promising direction is using actor critical DRL to optimize the MDP, where the values that are being predicted are the probabilities of a transition in the MDP.

In the third study, graphs will be used to represent a supply chain plan as a graph of dependencies between procurement, production, and other orders. Graph similarity will be used to determine the similarity between one supply chain plan and another, historical, supply chain plan. This similarity, as well as the outcome of the historical plan in terms of total supply cost, nervousness or the likelihood of an unexpected event occurring, can be used as input to the neural network that is used in the DRL optimization.

4.4 Relevant literature for the project, with separate citation of relevant literature of the research group and data sources

Names in **Boldface** are members of the research group.

E. Bargiacchi, D.M. Roijers, A. Nowé (2020). AI-Toolbox: A C++ library for Reinforcement Learning and Planning (with Python Bindings). Journal of Machine Learning Research 21 (102), pp. 1-12.

G. Brockman, V. Cheung, L. Pettersson, J. Schneider, J. Schulman, J. Tang, W. Zaremba (2016). Openai gym. arXiv preprint arXiv:1606.01540.

B. Cals, Y. Zhang, **R. Dijkman**, C. van Dorst (2021). Solving the Order Batching and Sequencing Problem using Deep Reinforcement Learning. Accepted for Publication in: Computers and Industrial Engineering.

P.S. Castro, S. Moitra, C. Gelada, S. Kumar, M.G. Bellemare (2018). Dopamine: A Research Framework for Deep Reinforcement Learning. arXiv preprint arXiv:1812.06110.

V. Gumuskaya, **W. van Jaarsveld, R.M. Dijkman**, P.W.P.J. Grefen, A. Veenstra (2020). Integrating stochastic programs and decision trees in capacitated barge planning with uncertain container arrivals. Submitted to: Transportation Research Part C.

W. van Jaarsveld (2020). Model-based controlled learning of MDP policies with an application to lost-sales inventory control. arXiv:2011.15122.

E. Peer, V. Menkovski, Y. Zhang, W.J. Lee (2018). Shunting trains with deep reinforcement learning. In 2018 IEEE international conference on systems, man, and cybernetics (SMC), pp. 3063-3068.

M. Plappert (2016). Keras-RL. Available online: https://github.com/keras-rl/keras-rl.

Z. Qin, X. Tang, Y. Jiao, F. Zhang, Z., Xu, H. Zhu, J. Ye (2020). Ride-Hailing Order Dispatching at DiDi via Reinforcement Learning. INFORMS Journal on Applied Analytics 50(5), pp. 272-286.

5. Relevance

5.1 For the European Supply Chain Forum

The project will be embedded in the High-Tech Community of the European Supply Chain Forum (ESCF). Studies will be performed with industry partners from that community with whom there already is a collaboration. For each study a workshop will be organized in collaboration with the ESCF, during which results from the study are presented.

5.2 For the IE&IS department

The goal of the project – optimizing operational (supply chain) processes – fits directly with the mission of the IE&IS department. The project is embedded in two of the groups of the department, the Information Systems and the Operations Planning Accounting and Control group, and relies on methods that are both studied and taught in both groups. The results from the projects can be used in knowledge exchange within and between the groups and the department as a whole. Potentially, results from the project and data sets that are collected during the project can be used in (project-based) courses that are taught in the department.

5.3 For EAISI

The project will be embedded in the EAISI AIMM Lab. Within the lab research methods will be discussed and results will be shared. Datasets may also be shared, depending on the precise confidentially agreements that are made within the project consortium. The possibilities of creating a follow-up project will also be discussed in the Lab.

1. Title of the PhD project

From feared competitor to trusted companion: understanding and enhancing trust in AI over time

2. Brief summary of the main research issue (max. 200 words)

Artificially Intelligent systems are becoming both much more pervasive and better. The interaction between the human planner and AI systems is far from hassle-free, though: on the one hand, AI-generated decisions are not trusted and overridden when they should have been left alone. On the other hand, AI-systems are trusted when they should not have been.

The literature has suggested several factors that influence the trust that a planner has in AI systems. Some of those factors are related to the planner (experience and expertise, for instance), some related to the system (transparency, reliability, fairness, …), and some related to the context in which the interaction takes place (high-risk vs. low-risk decisions, complex vs. more standard). An overlooked issue is that in many organizations, planners interact with the AI system repeatedly. This causes that, as planners interact more often, how they feel about and behave towards the system becomes more and more dependent on their experience with the system (and less dependent on these more often studied initial factors). **This project focuses on trust in AI-systems over time and how past interactions of the planner with the AI-system shape future interactions**.

3. Composition of the research group

Name, title(s)	Role (promotor/ (daily) supervisor/	Discipline	To the account of	Hours / week
Prof dr Chris Snijders	Promotor / supervisor	Decision-making, Trust, Human-Data Interaction	HTI	1.5
Dr Gerrit Rooks	Daily supervisor	Adoption of (technological) Innovation, Contextual psychology	HTI	2
Dr Martijn Willemsen	Supervisor	Human-Data Interaction, Explainable AI	HTI	1

4. Description of the project (1-2 pages)

4.1 Specification of the main research problem (i.e., key research problems and research aims)

More and more, human employees will have to work side-by-side with algorithms, and human planners are no exception (Fahimnia et al., 2019). The intuitive foundations of fruitful cooperation between humans and algorithms are certainly there. Planners have experience, expertise, and a trained intuition to guide them in making the right decisions. They can react to unexpected events (, whereas algorithms benefit from their flawless access to earlier data and consistency in calculating predictions. The daily practice of human-algorithm interaction does not reflect this win-win scenario, though (Dietvorst, 2015). Humans can be overconfident or rely on faulty intuitionscam; algorithms can miss the mark because of poor data input, overtraining, or a design that is too rigid to account for new developments. Moreover, the exact benefits of expertise and intuition in decision-making are unclear, to say the least (Tazelaar and Snijders, 2013; Kahneman and Klein, 2009). The literature is somewhat in favor of increased use of algorithmic models (Dawes et al., 1989; Grove et al.,1996), essentially claiming that algorithms are generally underused, but there is also evidence of misplaced trust in algorithms in several cases (Silver, 2012).

Key to the human-algorithm interaction is the amount of (justified) trust of the algorithm's user. Decades of trust-research have shown that humans can behave in peculiar ways when they have to hand over the control of the situation to others (van Lange et al., 2017; Raub and Snijders, 1997). They rely on their judgments too much, react to cheap signals, and generally have a tough time in arriving at behavior that appropriately judges the trustfulness of other people or other institutions. Algorithms are not likely to be an exception (cf. Snijders and Keren, 2001; Cook et al., 2009).

Whether planners are willing to trust an algorithm depends on several factors. The first factor is individual differences: some planners are more inclined to trust than others. Those who are more experienced, for instance, are less likely to follow algorithmic advice. The second factor considers the algorithm's characteristics: some algorithms are more likely to be trusted than others. For instance, algorithms that are (known to be) more accurate, or created by a reputable source, are trusted more. Third, contextual effects are important as well. In some circumstances, algorithms are trusted less. For instance, when life-or-death decisions or high accountability are an issue (in which case usually the human needs to take the final decision). Team composition or organizational culture have also been proposed to have an effect (cf. the proposed Ph.D. project "*Context matters: optimizing shared decision making*" of Le Blanc, vd Calseyde, Ulfert). Obviously, one could consider Interactions between these factors. For instance, more experienced humans might be less willing to trust an algorithm, but only when the algorithm is not near-perfect.

4.2 Scientific importance and relevance of the project (i.e., innovative aspects, embedding in literature, added-value)

How trust in algorithms evolves as a consequence of repeated interactions with the algorithm has been largely neglected, in part because the data are rare. There is a lot of literature on trust in repeated human-human interaction, though. We know that the more humans interact in a given setting, the more their perceptions and subsequent behavior are *not* guided by their initial ideas or feelings about the technology, but instead by what they see happening while they experience how the algorithm is predicting or suggesting. This interaction is complicated by the fact that trust is hard to gain but easy to lose. How can we create algorithms in such a way that algorithms receive the trust they deserve when they do but are overridden when they do not deserve this trust. It is this interplay that is crucial but ill-understood. Standard theories of technology acceptance, such as the literature about the diffusion of innovations, the theory of planned behavior, or the technology acceptance model, say little, if anything, about these matters.

4.3 Research methodology (e.g., research procedure, research design, models, sample, measures, statistics)

We distinguish the following phases in the research cycle.

1. **Combining the literature on trust in repeated interactions with the literature on trust in algorithms** into a model of factors that influence trust over time. Whereas there is a lot of literature on trust and cooperation in repeated interaction, virtually all of it consider human-human interaction. The literature on trust in algorithms is starting to materialize but hardly ever considers the repetition of the interaction. The first phase therefore consists of combining both literatures and deriving a comprehensive framework for trust in algorithms in repeated interaction.
2. Running a set of **behavioral experiments with students** to test and adapt the framework. Currently, such experiments are already being conducted in several Bachelor End and Master

Thesis research projects. Data from these experiments can be used to have the Ph.D. make a running start.

3. **Behavioral experiments / field studies with professionals**. Whenever possible, we want to see planners interact with algorithms in their daily work routines to further fine-tune the understanding of the human-algorithm interaction. Currently, we are collaborating with CIZ (Centrum Indicatiestelling Zorg), where human professionals are guided by algorithmic advice but need to make their own decisions. Analyses of more than 300,000 (repeated) interactions of CIZ-professionals with algorithmic advice will allow tests of fine-grained hypotheses about the development of trust over time. Whenever possible, we want to run such field studies, conditional of course, on cooperation of a focal organization.
4. **Design guidelines.** Finally, we want to develop guidelines that facilitate the usability, acceptance, efficiency, and effectiveness of the (implementation of) algorithmic advice in the work process of planning professionals.

4.4 Relevant literature for the project, with separate citation of relevant literature of the research group and data sources

Research group publications

Cook, K. S., **Snijders**, C., Buskens, V., & Cheshire, C. (Eds.). (2009). eTrust: Forming relationships in the online world. Russell Sage Foundation.

Kiconco, R. I., **Rooks**, G., & **Snijders**, C. (2020). Learning mobile money in social networks: Comparing a rural and urban region in Uganda. Computers in Human Behavior, 103, 214-225.

Raub, W., & **Snijders**, C. (1997). Gains, losses, and cooperation in social dilemmas and collective action: The effects of risk preferences. Journal of Mathematical Sociology, 22(3), 263-302.

Snijders, C., & Keren, G. (2001). Do you trust? Whom do you trust? When do you trust?. In Advances in group processes. Emerald Group Publishing Limited.

Snijders, C., & Keren, G. (2019). Determinants of trust. In Games and Human Behavior: Essays in Honor of Amnon Rapoport (pp. 355-385). Taylor and Francis Ltd.

Solano, G., & **Rooks**, G. (2019). When do businesses innovate in a developing country?. Business and Development Studies: Issues and Perspectives, 381.

Tazelaar, F., & **Snijders**, C. (2013). Operational risk assessments by supply chain professionals: Process and performance. Journal of Operations Management, 31(1-2), 37-51.

Relevant literature

Dawes, R. M., Faust, D., & Meehl, P. E. (1989). Clinical versus actuarial judgment. Science, 243(4899), 1668-1674.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 114.

Fahimnia, B., Pournader, M., Siemsen, E., Bendoly, E., & Wang, C. (2019). Behavioral operations and supply chain management–a review and literature mapping. Decision Sciences, 50(6), 1127-1183.

Grove, W. M., & Meehl, P. E. (1996). Comparative efficiency of informal (subjective, impressionistic) and formal (mechanical, algorithmic) prediction procedures: The clinical–statistical controversy. Psychology, public policy, and law, 2(2), 293.

Kahneman, D., & Klein, G. (2009). Conditions for intuitive expertise: a failure to disagree. American psychologist, 64(6), 515.

van Lange, P. A., Rockenbach, B., & Yamagishi, T. (Eds.). (2017). Trust in social dilemmas. Oxford University Press.

Rogers, E. (1962) Diffusion of innovations. New York: Free Press of Glencoe.

Silver, N. (2012). The signal and the noise: the art and science of prediction. Penguin UK.

Relevant research projects / available data

Trust in Algorithms Experiment Set. A set of experiments on how humans interact with algorithms in repeated interaction, following a standardized format. Currently, we have four data sets of (under-analyzed) experimental data for the project to make a running start with.

Trust in Algorithms at CIZ. A data set of 300,000+ decisions of CIZ-professionals, evaluating budgets for personal care with the help of an algorithm.

5. Relevance

5.1 For the European Supply Chain Forum

As we have experienced firsthand from interacting with (ESCF and other) companies that use predictive models or algorithms of sorts, many companies struggle with finding the right way to integrate these in their work processes, for all kinds of reasons. That employees will have to deal with AI systems that, at least some of the time and in some cases, are smarter than they are, will become more frequent and more salient. Even tasks that were once considered the typical domain of the experienced and knowledgeable human are being transformed into tasks that can be tackled by AI, or helped by AI systems. The project will contribute to a better understanding of how trust in algorithms evolves over time, which allows the development of guidelines for the implementation and successful (further) adoption of AI in ESCF's partner organizations.

5.2 For the IE&IS department

Considering how humans interact with technology is a key topic in the Humans and Technology Center, just as in the Logistics and its Interfaces theme, for obvious reasons. The project will connect with a growing group of researchers within HTI, HPM, P&E, and OPAC who consider human-AI collaboration in a broad sense, and is set up in such a way that it complements the PhD proposal "Context matters: optimizing shared decision making" by LeBlanc, vd Calseyde, and Ulfert. For this group of researchers, particularly the connection with organizations that allows the collection and measurement of actual behavior (and perhaps also some experimenting) in a real-life setting will substantially increase the impact of this research, as there is not a lot of field evidence around.

5.3 For EAISI

The project fits seamlessly with EAISI's key domain 2 (Humand and human-centered AI) and the research challenges posed there. Instead of a technology driven push of AI, human-centered AI emphasizes the need for behavioral insights into the interaction between humans and AI-systems, from a broader perspective than just the technology. To make AI work for and with humans, the human and her interaction with the technology have to be part of the research cycle, not an afterthought.

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

1. Title of the PhD project

Widening the frame: Rational choice beyond a given utility function

2. Brief summary of the main research issue (max. 200 words)

Supply chain and logistics planning problems can be seen as optimisation problems that require collecting as much relevant information as possible, determining possible choices, and selecting the action with the highest expected utility. They thus lend themselves to AI solutions: "AI has adopted the standard model: we build optimising machines, we feed objectives into them, and off they go." (Russell 2019, 172). "Rational choice" in this sense assumes a *given* utility function. But apart from well-known problems with rational choice in real-world environments (e.g. uncertainty, dynamic changes, other agents, non-discreteness of actions), we know from the human example that highly complex choices in real-world environments require considering which utility function to use, e.g. whether the utility function used needs to change or be overruled. Humans are able to *change the frame* of reference and include additional factors (e.g. the health of employees) or even to conclude that maximal expected utility is not the right criterion (e.g. because an action would be unjust). The supply chain and logistics planning problems are a fine place for a case study of this frame problem in a practical environment: When and how can a system say: "I should not decide this with my given utility function, I should change the frame"?

3. Composition of the research group

Name, title(s)	Role (promotor/ (daily) supervisor/	Discipline	To the account of	Hours / week
Müller, Vincent (Prof.)	Promotor	Philosophy	P+E	1
Zednik, Carlos (Assistant Prof.)	Supervisor	Philosophy	P+E	4
Fahland, Dirk (Assoc. Prof.)	Co-Promotor	CS	CS	1

4. Description of the project (1-2 pages)

4.1 Specification of the main research problem (i.e., key research problems and research aims)
What are the cases where a rational decision system needs to go beyond the given utility function (or goals), how can such a system detect these, how can it respond, how can we be sure that the system is under control while it makes these steps? When do we need a human in the loop of the decision, and when a human on the loop, or no human at all – because the system will alert if it detects a problem with its own utility function. This discussion will gain from the discussions of "control" and "autonomy" generally (Santoni de Sio & van den Hoven 2018), in the military context of automated weapons, e.g. (Simpson & Müller 2016) (Verdiesen, Santoni de Sio, & Dignum 2021), and in security-relevant applications (Christen et al. 2017).
To illustrate the notion of "frame", consider a foot soldier and the general of an army. Each of them is good at their task, but the tasks are different: The task of the foot soldier is to find good instrumental ways to follow orders and achieve the utility function he is given. By contrast, the general must competently move through frames of reference if they are to win the battle and the war. From her higher vantage point, she must *solve* problems in each sub-frame of the battle instrumentally, but also move up a level and define and discern and *decide* which utility functions matter now. At some point, the general may even realise that it is better to withdraw and loose a particular battle, in order to win the war.

4.2 Scientific importance and relevance of the project (i.e., innovative aspects, embedding in literature, added-value)

This is a case-study of rational choice in highly complex and dynamic environments where it is not possible to specify in advance which are all the potentially relevant factors for a choice. Thus, the classic "frame problem" (Shanahan 2016) is revived and reviewed here and regains practical relevance. It is also a contribution to the theory of "bounded rationality", i.e. the rationality that takes into account limited resources, thus not endlessly computing ever more optimal solutions for maximum expected utility (Russell 2016, 16ff). Bounded rationality will need to have a way to decide when to widen the frame. In a larger picture, the work on this PhD can contribute significantly to the incorporation of ethical choice into the classical theory of rational choice, as suggested in (Müller forthcoming, ch. 10).

4.3 Research methodology (e.g., research procedure, research design, models, sample, measures, statistics)

Work with practical problems in supply chain and logistics planning, and with computational models of these decisions, to specify structure of the problem. Reconstruction of the state of the art through literature research. Proposal of solutions to suitable samples for testing and development of the of the philosophical account. Systematic presentation of the shape of the frame problem and its relevance for AI ethics (Müller 2020) after these insights.

4.4 Relevant literature for the project, with separate citation of relevant literature of the research group and data sources

Christen, M., Burri, T., Chapa, J., Salvi, R., Santoni de Sio, F., & Sullins, J. P. (2017). An Evaluation Schema for the Ethical Use of Autonomous Robotic Systems in Security Applications. *University of Zurich Digital Society Initiative White Paper Series, 1*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3063617

Müller, V. C. (2020). Ethics of artificial intelligence and robotics. In E. N. Zalta (Ed.), *Stanford Encyclopedia of Philosophy* (Vol. Summer 2020, pp. 1-70). Palo Alto: CSLI, Stanford University.

Müller, V. C. (forthcoming). *Can machines think? Fundamental problems of artificial intelligence*. New York: Oxford University Press.

Russell, S. (2016). Rationality and intelligence: A brief update. In V. C. Müller (Ed.), *Fundamental issues of artificial intelligence* (pp. 7-28). Cham: Springer.

Russell, S. (2019). *Human compatible: Artificial intelligence and the problem of control*. New York: Viking.

Santoni de Sio, F., & van den Hoven, J. (2018). Meaningful Human Control over Autonomous Systems: A Philosophical Account. *Frontiers in Robotics and AI, 5* (15), 1-15. doi: 10.3389/frobt.2018.00015

Shanahan, M. (2016). The frame problem. In E. N. Zalta (Ed.), *Stanford Encyclopedia of Philosophy* (Vol. Spring 2016 edition). Palo Alto: CSLI, Stanford University.

Simpson, T. W., & Müller, V. C. (2016). Just war and robots' killings. *The Philosophical Quarterly, 66* (263), 302-322. doi: 10.1093/pq/pqv075

Verdiesen, I., Santoni de Sio, F., & Dignum, V. (2021). Accountability and Control Over Autonomous Weapon Systems: A Framework for Comprehensive Human Oversight. *Minds and Machines, 31* (1), 137-163. doi: 10.1007/s11023-020-09532-9

5. Relevance

5.1 For the European Supply Chain Forum

Theoretical insights into the rational choice process and bounded rationality. Incorporation of ethical concerns into that process – avoiding unfortunate surprises.

5.2 For the IE&IS department

New theory on an important detail of ethical choice, in connection with a practical and useful application.

5.3 For EAISI

As above, enabled by a link that only EAISI can make. Insights for other researchers in the group.