International Journal of Production Research

ISSN: 0020-7543 (Print) 1366-588X (Online) Journal homepage: www.tandfonline.com/journals/tprs20

Marrying math and mind: towards production planning systems for industry 5.0

Maryam Azani, Lijia Tan, Rob Basten & Ton de Kok

To cite this article: Maryam Azani, Lijia Tan, Rob Basten & Ton de Kok (2025) Marrying math and mind: towards production planning systems for industry 5.0, International Journal of Production Research, 63:13, 4864-4886, DOI: 10.1080/00207543.2024.2443800

To link to this article: https://doi.org/10.1080/00207543.2024.2443800

Published online: 27 Jan 2025.

INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH
2025, VOL. 63, NO. 13, 4864–4886
https://doi.org/10.1080/00207543.2024.2443800

Marrying math and mind: towards production planning systems for industry 5.0

Maryam Azani [a], Lijia Tan [a], Rob Basten [a] and Ton de Kok [a,b]

[a]Department of Industrial Engineering and Innovation Sciences, Eindhoven University of Technology, Eindhoven, Netherlands; [b]Centrum Wiskunde & Informatica (CWI), Amsterdam, Netherlands

ABSTRACT

How can a sophisticated Production Planning (PP) system help planners? To answer this question, we study the PP literature and focus on human-system interaction. We find that the PP literature mainly focuses on designing sophisticated algorithms. By synthesising forecasting and information system (IS) literature, we provide findings for designing a human-centred PP system. From the forecasting literature, we learn that certain biases and heuristics become relevant when humans work with systems. We categorise this literature into three system elements: information received, delivery system, and decision aid provided, as well as two human factors: cognitive limitations and capabilities. From the IS literature, we learn that different factors impact behaviour over the system acceptance and continued use phases. Behaviour is mainly impacted by the Perceived Ease of Use in the acceptance phase. The Perceived Usefulness mainly determines interventions to the solutions in the continued use phase. We combine the two phases distinguished in the IS literature with the three system elements distinguished in the forecasting literature and thus propose a two-phase × three-element matrix for designing human-centred systems, obtain findings that serve as guidelines for designing human-centred PP systems, and propose an agenda for future research in PP.

ARTICLE HISTORY
Received 31 January 2024
Accepted 3 December 2024

KEYWORDS
Production planning systems; human-system interactions; human-centric design; behavioural operations management; industry 5.0

1. Introduction

Modern systems have emerged to assist humans in PP. However, the performance outcomes of these systems are not solely determined by their analytical capabilities but rather by the interaction between humans and the system (Vijayakumar et al. 2022). PP is a decision-making process that involves long-term, medium-term, and short-term decisions to meet customer demand under uncertainty. Long-term decisions, such as planning for acquiring resources, are strategic and generally made annually with a planning horizon of more than 2 years. Medium-term decisions, such as resource utilisation planning, are tactical. Tactical decisions are generally made monthly with a planning horizon of 6 to 24 months. In contrast, short-term decisions, such as planning to meet day-to-day customer demand, are operational and generally made weekly or daily with a planning horizon of less than 6 months (Silver, Pyke, and Thomas 2016, 564). This study focuses on short-term decisions that involve frequent interaction between humans and the system.

The short-term PP process (see Figure 1) starts with short-term (demand) forecasting, which utilises historical demand as input. The forecasted demand is then used to generate a Master Production Schedule (MPS) that specifies what products to manufacture at a specific time and facility. Next, Material Requirement Planning (MRP) determines the raw materials required to realise the MPS. Once the materials are delivered, the production sequence is scheduled through Job-Shop Scheduling (JSS). Finally, customer orders are delivered, and any excess products, work in progress, and materials are stored in the inventory (APICS 2009). This study explicitly targets key processes within short-term PP: MPS, MRP, and JSS. Our emphasis on these three processes is also driven by the relatively limited research attention given to understanding the vital role of human-system interaction within these areas. For clarity, we refer to PP in the remainder of this paper to discuss the three targeted PP processes.

PP involves a series of decisions in a complex environment. This complexity can arise from uncertainties (uncertainty-induced complexity) or from dealing with multiple items, resources, relations, etc. (structural complexity) that should be taken into account when planning (Wiers and de Kok 2017). Uncertainty-induced complexity can have an internal or external source. Internal sources happen due to the activities occurring in the company, such as inaccurate forecasts, machine plan

CONTACT Maryam Azani m.azani@tue.nl Department of Industrial Engineering and Innovation Sciences, Eindhoven University of Technology, Eindhoven, Netherlands

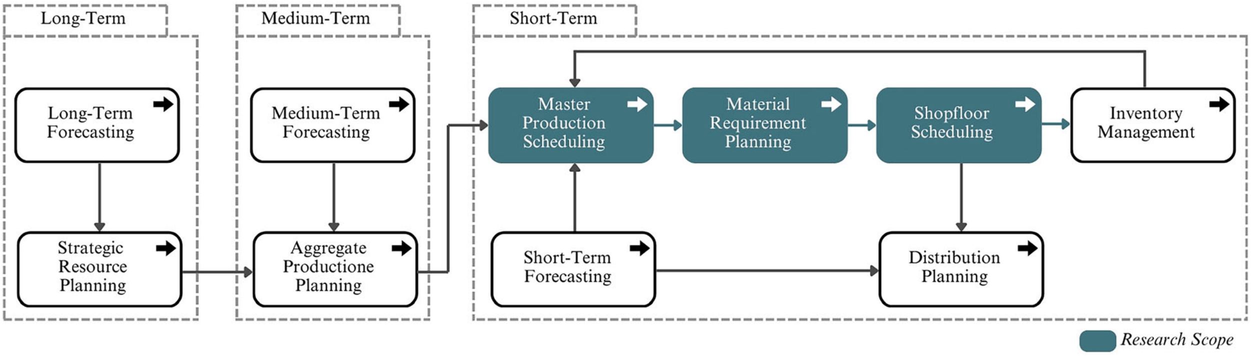


Figure 1. Production Planning Processes based on Silver, Pyke, and Thomas (2016).

overload, machine breakdown, quality inspection, etc. External sources result from supply chain activities, such as customers or suppliers (Guide Jr and Srivastava 2000). For instance, changes in lead time or configurations requested by customers and suppliers' late deliveries are examples of external uncertainty. Koh and Saad (2003) identify instances of uncertainty that impact the performance of companies.

In such complex and uncertain environments, both systems and humans are needed (Grosse et al. 2015; Lawrence et al. 2006). Systems can manage complexity well (Galbraith 1973). They are rigid and only possess a limited subset of information but can process it with greater efficiency and accuracy (Boyacı, Canyakmaz, and de Véricourt 2024). Besides, systems can be less bias-prone than humans (Liu, Yang, and Wen 2023). However, effective uncertainty management requires the joint efforts of humans and systems (Eriksson, Carlsson, and Olsson 2022; MacCarthy and Wilson 2003, 184). Kocsi et al. (2020) explain that certain production characteristics, such as the dynamic nature of demand in high-mix, low-volume manufacturing, make the use of systems alone challenging. Systems are not flexible and cannot adapt to changes or disruptions in the environment. For example, when suppliers fail to deliver, systems cannot update this on time. Systems use heuristics and miss many aspects of the real world, which can be compensated for by humans (Van Donselaar et al. 2010). Humans are flexible; they possess tacit knowledge missing in systems and can negotiate with the outside world (McKay and Wiers 2006, 28).

There are different perspectives on the relationship between humans and systems. Some studies take a competitive perspective on human-system interaction when they find systems outperform humans (e.g. Liu et al. 2019; Quiroga, Moritz, and Ovchinnikov 2019), while others promote a collaborative relationship in which systems have the need for human input (Kesavan and Kushwaha 2020; Van Donselaar et al. 2010). Figure 2 visualises a collaborative relationship between humans and systems. We refer to the system as a human-centred PP system that allows interactions with humans and leaves the final decision to humans. In the interactions, the human provides input to the system and receives recommendations from the system. Humans, as the final decision-makers, decide the production plan and their performance can be measured by service level, inventory cost, or other indices, which can differ across companies.

In Figure 2, we give two human factors related to human planners: cognitive limitations and cognitive capabilities (Daniel 2017, 23). The two factors influence humans' interaction with systems as well as their planning decisions. Cognitive limitations in human decision-making can be attributed to biases and information-processing constraints, such as limited working memory capacity. Cognitive capabilities can be attributed to heuristics and fast responsive decisions, such as planning decisions right after a supply chain disruption. An efficient human-centred PP system would be able to compensate for planners' cognitive limitations and utilise planners' capabilities. For instance, a system calculating an optimal scheduling plan can compensate for the computation limit of human planners, and a system allowing planners to set parameters utilises planners' intuition about the current state.

This paper aims to provide theory-driven guidelines for designing a human-centred PP system. This system is purposefully designed to adapt to humans' cognitive limitations and capabilities to provide effective support to human planners. We employ the three system elements developed by Zmud (1979), in which a system is split into three elements: information received, delivery system, and decision aid provided, to classify the specific system design. We have three reasons for utilising the elements to investigate PP systems. First, classifying designs into system elements helps designers anchor to the specific purpose. Second, human factors can play different roles as they interact with the elements of the system. Third,

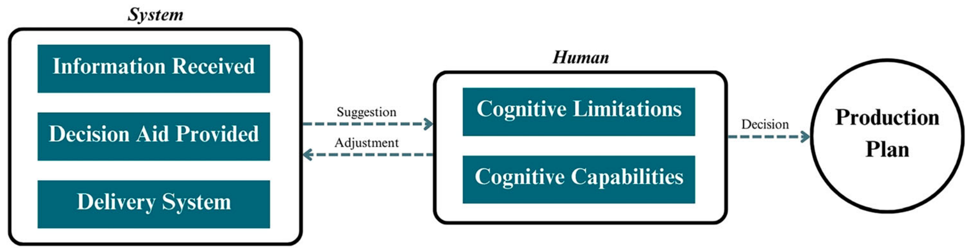


Figure 2. Human-System Interaction.

Table 1. Three System Elements based on Zmud (1979).

System Element	Purpose	Relevant Application
Information Received	'Information has value only when it reduces the uncertainty that pervades decision-making (King and Epstein 1976).' (Zmud 1979, *p*. 968)	Information on demand forecasts, inventory levels, and production capacity
Decision Aid Provided	'Decision aids are provided to overcome limitations inherent in human cognition and to ensure that available information is sensed and used.' (Zmud 1979, *p*. 968)	Simulation tools, inventory management models, and algorithms
Delivery System	'The convenience and ease of use of a system are considered as important to system usage as is the quality of the information received (Paisley 1968).' (Zmud 1979, *p*. 968)	Dashboard, user interface, and pop-up messages

breaking down a system into three elements makes our guidelines more actionable. According to Zmud (1979), information received relates to the information provided to planners, such as demand forecasts and real-time inventory levels. Decision aid provided refers to tools or techniques (e.g. models) used to overcome human cognitive limitations and ensure that available information is utilised effectively. The delivery system refers to the interface that connects the humans with the system. Table 1 provides examples of the purpose and application of each element. The *information received* is transformed into system suggestions through the *decision aid provided* and communicated to humans via a *delivery system*.

We find that there is a lack of attention to human factors when designing PP systems. Therefore, we continue to analyse the literature from other domains for insights. In operations research, research on human-system interaction has grown. Judgmental forecasting, with decades of research (see Lawrence et al. (2006)), has made a drastic contribution to understanding human-system interaction. Compared to PP research, judgmental forecasting is inherently less complex and more adaptable to various decision-making scenarios. Forecasting has a strong foundation in psychology and behavioural economics. Therefore, we examine the field of forecasting to identify key insights that can be translated into guidelines for designing effective PP systems. We categorise our insights into the three system elements of Zmud (1979) and two human factors of Daniel (2017, 23) to facilitate the translation.

Our review of PP and forecasting literature is not yet in relation to the human-system interaction over time. Therefore, we make use of IS literature to gain more insight into the human-system interaction over time. Planners' cognitive limitations can hinder their acceptance of the new system. For example, planners need to understand the system to some extent before they accept it (Eriksson, Carlsson, and Olsson 2022). In the IS literature, Davis's (1989) Technology Acceptance Model (TAM) provides a conceptual framework to address this challenge. The Perceived Usefulness (PU) and ease of use (PEOU) of the system shape humans' attitudes toward acceptance. Keil, Beranek, and Konsynski (1995) further develop this model and point out that human–system interaction involves two phases: System Acceptance (SA) and Continued Use (CU). This suggests that an effective human-centred PP system should not only be easy for planners to understand and accept initially but also encourage long-term, sustained use. Classifying system designs into these two phases allows us to provide precise guidelines for system designers based on the short-term and long-term needs of humans.

We combine the two phases obtained from IS literature with the three system elements summarised from PP and forecasting literature; we propose a two-phase × three-element matrix to structuralise the guideline for designing human-centred PP systems. Table 2 presents an overview of our PP findings structure, which are further discussed in detail in Section 5.

This paper has three contributions to theory and practice. First, we provide theory-driven guidelines on how to design human-centred PP systems by synthesising literature from forecasting and IS. Second, we contribute to the broader human-system interaction field by proposing a two-phase × three-element matrix (see Table 7). This matrix is designed by categorising literature from forecasting and PP based on system elements and IS literature based on human-system interaction journey phases. Our

Table 2. Two-phase × Three-element Matrix.

Phase	Element		
	Information Received	Delivery System	Decision Aid Provided
System Acceptance (SA)	Finding SA.1	Finding SA.2	Finding SA.3
Continued Use (CU)	Finding CU.1	Finding CU.2	Finding CU.3

proposed matrix serves as a high-level conceptual framework that provides a structured approach to guide the design of human-centred systems beyond the PP context, whereas the findings are the detailed application of this matrix for PP. Third, we provide an agenda for future research in PP that considers the interaction between humans and systems (see Table 8).

The remainder of this paper is structured as follows. Section 2 presents a systematic review of the existing literature on human-system interaction in the PP. Sections 3 and 4 discuss forecasting and IS research on human-system interaction, respectively. Section 5 synthesises literature from forecasting and IS disciplines and translates these insights into 1) findings for designing human-centred PP systems and 2) directions for future research in PP. Finally, in Section 6, we conclude this paper.

2. State-of-the-art literature on human-system interaction in production planning

As discussed in Section 1, PP is a complex decision-making process. Systems are designed to help planners in making these decisions. Designing a good PP system requires considering human factors. In this section, we conduct a systematic literature review on the human factors in PP literature by using the five-step approach of Wolfswinkel, Furtmueller, and Wilderom (2013): Define, Search, Select, Analyse, and Present. Our first step is to set criteria for inclusion and exclusion, identify relevant research fields, choose sources, and define search strings based on the review's goal. The second step is to search for literature that has the potential to be related to our topic of human-system interaction in PP. The third step is to select relevant literature and to refine the selected literature into the literature focusing on our topic. We do this in three sequential procedures screening by title, abstract, and full text, followed by forward and backward citation tracking (snowball method) (see Figure 3). The fourth step is to analyse the selected literature and group it into relevant categories: system element, human factor, and context. In the final step, we present the insights which will guide the design of a system for human planners.

The review approach of Wolfswinkel, Furtmueller, and Wilderom (2013) falls between the traditional narrative review approach of Baumeister and Leary (1997) and the structured, systematic literature review approach of Tranfield, Denyer, and Smart (2003). We have three reasons to use the Wolfswinkel, Furtmueller, and Wilderom (2013) approach. First, this approach is developed from the grounded theory, which has greater flexibility than other structured review methods. It allows authors to integrate new insights or unexpected findings during the review process. This is particularly important in complex, multidisciplinary, and underexplored fields such as behavioural PP. Second, despite this flexibility, Wolfswinkel, Furtmueller, and Wilderom (2013) maintain a structured approach. It categorises concepts and codes literature, which provides reproducible results. Third, the approach of Wolfswinkel, Furtmueller, and Wilderom (2013) enables the development of new theories from the data, while many review methods primarily summarise existing theories.

In the remainder of this section, we describe the steps of our systematic literature review and summarise the results. Section 2.1 provides details of Steps 1 through 4, followed by the presentation of the results per system element in Sections 2.2, 2.3, and 2.4.

2.1. Method

2.1.1. Step 1: define

Our search focuses on research in English that was published from 2000 onwards, specifically articles, review articles, books, and proceedings papers. The search covers relevant research fields in Engineering, Psychology, Computer Science, Mathematics, Behavioural Science, and Management.

We used Web of Science as our primary database and grouped our search strings into three categories: human factor, system element, and context (see Table 3). The search strings selected in the human factors category are specifically designed to capture the mental and cognitive capabilities of humans, as well as their limitations. Our review does not include investigating human ergonomic or physical capabilities. We based our search string selection in the system category on Zmud's (1979) categorisation of system elements, i.e. information received, decision aid provided, and delivery system. Similarly, for the context category, we selected relevant PP processes described in Section 1. Our search yielded 59,404 articles on the context of PP, of which 34,397 are related to designing PP systems. Only a small fraction of this literature (856 articles) discusses the crucial role of humans in PP.

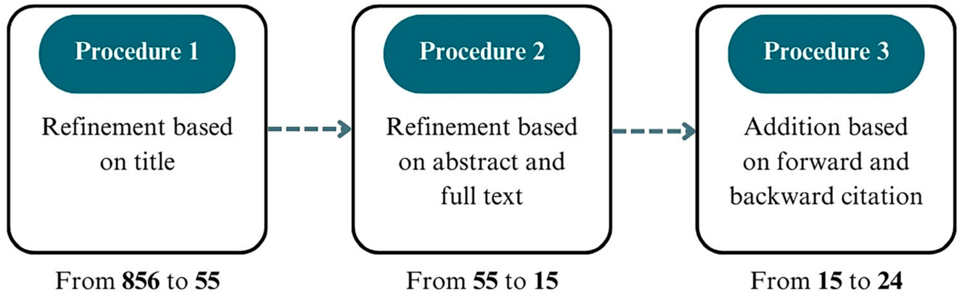


Figure 3. Procedures for the Selection of Focused Papers.

Table 3. Search String.

Category	Human Factor	System Element	Context
Search Strings	'Mental' 'Human Decision' 'Cognitive' 'Bias'	'System' 'Information' 'Algorithm' 'User Interface'	'Production Planning' 'Material Planning' 'Master Production' 'Job-Shop'

2.1.2. Step 2: search and select

From the initial pool of 856 articles, we selected those that have at least one combination of two strings in the title: 'Human/planner/cognitive/behaviour' and 'production, plan/manufacturing/lead-time/scheduling'. These strings have undergone iterative selection to minimise the occurrence of false positives and false negatives in our sample. This approach limited subjective evaluation and resulted in a sample of 55 papers. We then examined the abstract and full text and excluded irrelevant literature (e.g. papers focusing only on ergonomics, human-robot collaboration, or planning in different application areas). This refined our sample to 15 relevant articles. We added nine additional articles through forward and backward citation searches, resulting in a final sample of 24 papers (see Figure 3).

2.1.3. Step 3: analyse

As our primary purpose is to review human-system interaction in PP literature, we classify the selected literature into three categories: context, human factor, and system element. Context is divided into production planning, job-shop scheduling, material planning, and master production scheduling (as explained in Section 1). Humans have capabilities and limitations in their decision-making (Daniel 2017, 23). We analyse human factors for both cognitive limitations and capabilities. System elements are classified according to Zmud's (1979) system design characteristics into information received, delivery system, and decision aid provided. Table 4 provides a summary of the articles and their main categories. In Sections 2.2, 2.3, and 2.4, we discuss our insights from the literature regarding the information received, delivery system, and decision aid provided.

2.2. Information received

Effective design of PP systems requires thoughtful consideration of human information processing capability (Wiers and de Kok 2017, 171). For instance, providing excessive information might lead to poor performance. Arnold (2018) emphasises the importance of considering human cognitive capability when designing PP systems. The cognitive capability includes how the human brain processes information, prioritises activities, selects information, and so on.

The frequency of information updates in a PP system can affect the decisions made by planners. Haeussler et al. (2021) examine a lead-time updating trap in which suppliers frequently update their lead times to protect themselves from possible penalties or late deliveries. However, they unintentionally trigger a chain reaction that leads to overproduction, excess inventory, and other inefficiencies. The frequent lead-time updates result in a vicious circle of human interventions. Besides the frequency, the content of information also has an impact on the decisions. Letmathe and Zielinski (2016) conduct a lab experiment to evaluate the performance of three types of content for feedback (financial, non-financial, and mixed) in a repeated PP game. They find that individuals' information processing capabilities, specifically their work experience and education, must be considered when choosing the feedback content.

The information provided by PP systems should enable planners' decisions. Lauer et al. (2020) study the most effective human-system interaction approach from three options: 1) no interaction between humans and the system, 2) selecting a system solution based on the human's preferred risk attitude, or 3) questioning the system about its assumptions. They conclude that different types of human-system interaction approaches impact the system's acceptance differently. Fransoo and Wiers (2008) argue that the lack of necessary information in PP systems is the primary reason for significant human adjustments, particularly in complex tasks. They propose that adjustments to final system solutions could be replaced with parameter changes if the

Table 4. Summary of State-of-the-art Literature on Human-System Interaction in Production Planning.

			System Element			Human Factor	
Author	Year	Research Method	Information Received	Delivery System	Decision Aid Provided	Limitations	Capabilities
Christova et al.	2003	Conceptual Model			✓		✓
Zoryk-Schalla et al.[†]	2004	Empirical Study			✓	✓	
Wiendahl et al.	2005	Conceptual Model			✓	✓	
Stowasser*	2006	Lab Experiment		✓		✓	
Fransoo & Wiers[†]	2008	Empirical Study	✓			✓	
Silva*	2009	Empirical Study			✓		✓
Moscoso et al.[†]	2010	Empirical Study			✓	✓	
Schock et al.[‡]	2010	Empirical Study		✓		✓	
Bendul & Knollman	2016	Empirical Study		✓		✓	
Letmathe & Zielinski	2016	Lab Experiment	✓			✓	
Brolin et al.*	2017	Lab Experiment	✓			✓	
Graessler & Pöhler*	2017	Conceptual Model			✓	✓	✓
Hernes & Bytniewski	2017	Conceptual Model	✓				✓
Wiers & de Kok	2017	Conceptual Model	✓	✓	✓	✓	✓
Arnold	2018	Conceptual Model	✓	✓		✓	
Oberc et al.	2018	Field Experiment			✓	✓	
Yahouni et al.*	2018	Lab Experiment		✓		✓	
Bendul	2019	Empirical Study		✓		✓	
Lauer et al.[‡]	2020	Lab Experiment & Empirical Study	✓	✓		✓	
Haeussler et al.[†]	2021	Lab Experiment	✓			✓	
Merten et al.*	2022	Empirical Study			✓		✓
Rožanec, Lu, et al.	2022	Conceptual Model		✓	✓		✓
Vijayakumar et al.	2022	Conceptual Model	✓	✓	✓	✓	
Wong & Chui*	2022	Conceptual Model			✓	✓	✓

[‡] denotes a focus on MPS (Master Production Scheduling), [†] denotes a focus on MRP (Material Requirements Planning), and * denotes a focus on JSS (Job-Shop Scheduling). Papers without symbols have a general focus on Production Planning.

necessary feedback for changing system parameters is available.

Despite humans having cognitive limitations, using heuristics to simplify large amounts of information has been highly beneficial. Hernes and Bytniewski (2017) explain that different agents in a manufacturing planning module may generate contradictory production plans based on their embedded models. This leads to time-consuming and error-prone work for human planners who must manually assess and select the plans. However, the system can imitate human information processing and heuristics to quickly consolidate all plans (Vijayakumar et al. 2022).

Conclusion: The importance of precise and timely information is well understood, especially in the context of human-system interaction. Nevertheless, too much information exhausts humans' cognitive capabilities and reduces overall performance as humans struggle to distinguish relevant from irrelevant information. When information updates occur too frequently, such information distracts decision-makers from focusing on important details. Therefore, there should be a balance between the amount of information provided and human cognitive limitations and capabilities.

2.3. *Delivery system*

The delivery system (or interface) is the presentation format of the system's output to the humans. A well-designed delivery system increases human experience and helps with decisions effectively. Bendul (2019) and Bendul and Knollman (2016) explain that adverse performance outcomes arise when humans misinterpret system states and are unaware of systems' fundamental KPIs. A proper interface assists planners in dealing with disturbances in highly uncertain situations. Yahouni et al. (2018) propose a human-system interface model that provides real-time information about production status, disruptions, and scheduling conflicts to improve the interaction between a human planner and a system. The experimental results indicate that the interface significantly improves planners' scheduling decisions in highly uncertain situations.

Visualised information empowers planners to make quick and reasonable decisions (Schock et al. 2010). In a study by Brolin, Thorvald, and Case (2017), participants were asked to process information presented in different formats, such as photographs or written text. The researchers find that using photographs reduces the information process time and the cognitive load. By using the photographs, participants could focus on critical information without being distracted by unrelated details. Stowasser (2006) develop a visualisation system for planners to monitor distributed manufacturing processes. It features a dynamic 3D visualisation and window-based interface (a conventional format of information representation), allowing humans to monitor real-time information on production processes. The author evaluates the system's usability and its psychological impact and finds that the hybrid interface design (3D visualisation and window-based interface) effectively improves decision-making efficiency.

Conclusion: The delivery system, i.e. how information is presented - its style and format - directly affects cognitive load, processing time, user satisfaction, and decisions. A well-crafted interface makes complex system outputs easier to understand. For instance, visuals can clearly and concisely convey information. Nevertheless, a balanced combination of text and visuals is often the best approach for assisting human decisions.

2.4. Decision aid provided

The decision aid provided refers to the underlying model or algorithm of the system. On the one hand, the underlying model of the system determines the quality of decision aid provided. On the other hand, human planners are the final decision-makers in the process (Moscoso, Fransoo, and Fischer 2010). Humans are cognitively limited. Oberc et al. (2018) recommend developing advanced systems that crosslink data across various systems within a company to restrict human involvement in operational-level tasks. Zoryk-Schalla, Fransoo, and de Kok (2004) explain that human overconfidence impacts their decisions when intuitions conflict with the system solutions. As a result, advanced planning systems may not be able to assist planners as effectively as the systems designer expects. Designing PP systems needs to incorporate human biases.

Contrary to these biases, human planners have a good knowledge of how to deal with problems in complex PP environments. Combining human knowledge with planning and scheduling rules to design an algorithm achieves better planning results. Wiers and de Kok (2017, 168) suggests automating routine tasks. However, when there are complex decisions, humans should be the frontiers in making decisions. Merten, Hütt, and Uygun (2022) find that human tacit knowledge about parameters is essential for handling complex tasks, such as in steel manufacturing. They develop a method to identify the planning parameters commonly prioritised by human planners and incorporate this information into the system. Silva (2009) introduces an algorithm that integrates human expertise with formal planning rules. This approach incorporates both soft (informal) and hard (formal) constraints to formulate feasible plans. Planners have the flexibility to adjust soft constraints based on their expertise, while hard constraints remain immutable.

Systems should be designed taking human needs into account (Wiendahl et al. 2005). Wong and Chui (2022) develop such kind of aid called cognitive engine process controller. Their system streamlines large amounts of information and suggests appropriate next steps to the human operator, who then manages the process based on a limited number of recommended steps. Additionally, the system allows for alternative methods to be used, providing flexibility to humans when necessary. Graessler and Pöhler (2017) propose the development of a human digital twin to overcome delays in human input. This cyber-physical device mirrors human properties, preferences, work schedules, and skill sets. The human digital twin optimises the decisions by processing information based on individual preferences. Individuals can control their digital twin via a mobile device, allowing them to participate actively in decision-making. Similarly, Rožanec et al. (2022) propose using actionable cognitive twins, which are enhanced digital twins that use knowledge graphs and AI models. The knowledge graph contains domain-specific knowledge on entities, interrelationships, and potential decision-making options to facilitate decision-making.

Conclusion: Advanced planning systems are known for their performance. Nevertheless, human involvement should not be undervalued. Humans possess an intuitive understanding and insight that often surpasses the capabilities of the most sophisticated systems. Thus, effective decision-making should incorporate both the flexible rules generated by human expertise and the formal constraints of algorithms. Systems must be adaptive and customised according to human requirements. They should allow for human intervention and alterations based on individual expertise. While systems excel at handling repetitive tasks swiftly and accurately, consequential decisions require incorporating human expertise.

3. Human-System interaction in forecasting literature

Forecasting refers to the process of estimating and predicting immediate future production requirements by analysing historical demand information. In forecasting, considering humans or systems individually leads to inaccurate forecasts (Arvan et al. 2019; Lauer and Wieland 2021; Perera et al. 2019). Forecasting literature highlights potential biases when human planners work with systems. These insights can be used when designing PP systems.

Human biases can be categorised as intentional or unintentional (Oliva and Watson 2009). Intentional biases are deliberate decisions in a specific direction that

Table 5. Summary of State-of-the-art Literature on Human-System Interaction in Forecasting.

			System Element			Human Factor	
Author	Year	Research Metod	Information Received	Delivery System	Decision Aid Provided	Limitations	Capabilities
Harvey & Bolger	1996	Lab Experiment		✓		✓	
Goodwin	2000	Lab Experiment			✓	✓	
Parikh et al.	2001	Lab Experiment	✓			✓	
Webby et al.	2005	Lab Experiment	✓			✓	
Lee et al.	2007	Lab Experiment	✓			✓	✓
Franses & Legerstee	2011	Empirical Study			✓		✓
Franses & Legerstee	2013	Empirical Study			✓		✓
Seifert & Hadida	2013	Field Experiment			✓		✓
Dietvorst et al.	2015	Lab Experiment		✓	✓	✓	
Fildes & Petropoulos	2015	Conceptual Model	✓		✓	✓	✓
Green & Armstrong	2015	Conceptual Model			✓	✓	✓
Seifert et al.	2015	Field Experiment	✓			✓	
Theocharis & Harvey	2016	Lab Experiment		✓		✓	
Alvarado-Valencia et al.	2017	Empirical Study			✓		✓
Baecke et al.	2017	Empirical Study			✓		✓
Dietvorst et al.	2018	Lab Experiment			✓	✓	
Katsikopoulos et al.,	2018	Conceptual Model			✓	✓	✓
Kusev et al.	2018	Lab Experiment		✓		✓	
Tong et al.	2018	Lab Experiment	✓			✓	
Goodwin et al.	2019	Lab Experiment	✓			✓	
Theocharis et al.,	2019	Lab Experiment		✓		✓	
Dietvorst & Bharti	2020	Lab Experiment			✓	✓	
Fildes & Goodwin	2021	Empirical Study			✓	✓	
Jung & Seiter	2021	Lab Experiment			✓	✓	
Leffrang & Müller	2021	Lab Experiment		✓		✓	
Satopää et al.	2021	Mathematical Model	✓			✓	
Chacon et al.	2022	Lab Experiment			✓	✓	
Daschner & Obermaier	2022	Lab Experiment			✓	✓	
Feiler & Tong	2022	Lab Experiment	✓			✓	
Himmelstein & Budescu	2023	Lab Experiment			✓	✓	

deviate from rational evaluations or objective assessments. Intentional biases may be driven by the misalignment of incentives and power. For example, high-priced products cause humans to make more frequent adjustments (Khosrowabadi, Hoberg, and Imdahl 2022). In contrast, unintentional bias occurs without deliberate intentions. For example, individuals who perceive a system as insufficient to reflect reality adjust the suggestions unintentionally (Boulaksil and Franses 2009).

We categorise the forecasting literature based on system elements and human factors. We use Zmud's system elements: information received, delivery system, and decision aid provided for our system element categorisation. Our analysis covers human factors, including both cognitive limitations and capabilities. Table 5 presents an overview of the state-of-the-art literature on forecasting. In Sections 3.1 through 3.3, we discuss the literature related to each of the three system elements: information received, delivery system, and decision aid provided, respectively.

3.1. Information received

The relevance and volume of the information provided to decision-makers influence forecasting accuracy (Webby, O'Connor, and Edmundson 2005). Human decision-makers often exhibit a cognitive bias, overvaluing the information they possess while undervaluing the information they lack (Tong, Feiler, and Larrick 2018). Therefore, selecting what information to present to decision-makers is an important question. Feiler and Tong (2022) find that a high volume of information (e.g. nine data points versus one) can lead to noisy interpretation and degraded forecasting performance. Reducing noise from useful information is effective in improving forecasting accuracy (Satopää et al. 2021). However, identifying what constitutes noise is highly dependent on the specific context. For instance, in fast-paced industries such as fashion, historical demand might be noise as the trends change rapidly (Seifert et al. 2015).

Forecasting systems that contain poor-quality information require significant human intervention. Poor information quality refers to information that contains inaccuracies, inconsistencies, and errors that undermine its reliability for its intended purpose. Fildes and Petropoulos (2015) discuss that when the information is of poor quality, relying solely on automated forecasting systems can lead to inaccurate results. As a result, human expertise and intuition become even more critical. Humans can make analogies based on past experiences or knowledge from a different domain to deal with the issue of poor-quality information (Lee et al. 2007).

Framing and the type of information provided to the planners impact their behaviour and judgements. Parikh, Fazlollahi, and Verma (2001) compare the effectiveness of informative and suggestive information. Informative recommendations provide humans with detailed and relevant information, which helps them to learn and understand the decision-making process. They find that informative recommendations are more effective when the objective is to assist humans in learning. On the other hand, when the objective is to improve decision quality, suggestive information that prompts humans to consider a particular option is more effective. Goodwin, Gönül, and Önkal (2019) look into two types of information, i.e. optimistic and pessimistic scenarios with time series forecasts. They explain that planners presented with optimistic or pessimistic scenarios, in addition to time series data, exhibit greater deviation from optimality due to less precise point forecasts.

Conclusion: The forecasting accuracy of decision-makers is influenced by the relevance and volume of information. Identifying and reducing noise from high volumes of information can improve forecasting accuracy. When information is poor quality, human contribution to decision-making becomes more important.

3.2. Delivery system

The delivery system allows humans to interact with the system through graphical elements. A well-designed interface can empower human decision-making by providing them with a good experience of interacting with the system. Taking human cognitive processes into account while designing an interface is important. When the information provided is clear and intuitive, decision-makers can easily understand and make a good forecast decision.

The framing and format of the information presented to forecasters influence their decision-making and performance. Different frames and formats are beneficial depending on the context and information. For linearly trended series, graphical presentation proves more effective than tabular form. Graphical presentations reduce the tendency to underestimate trends when the series are linearly trended. Conversely, for series that do not follow a specific trend, a tabular presentation yields better performance. For such a series, a graphical presentation leads to over-forecasting and inconsistency (Harvey and Bolger 1996). Kusev et al. (2018) find that when events are presented sequentially one after the other, forecasting accuracy is improved. However, it leads to worsened average estimation. In contrast, when events are viewed simultaneously, average estimation accuracy is improved, but the recent events are neglected.

The delivery system should consider human biases. An ineffective delivery system design can increase the adverse impact of biases on performance. For instance, human decision-makers anchor on their previous decision or demand information. This behaviour still occurs when forecasts are untrended and independent (Theocharis, Smith, and Harvey 2019). In fact, humans detect positive sequential dependence between forecasts regardless of the fact that such forecasts may be independent. This effect is stronger when they are presented with visuals, e.g. line graphs. To handle the human tendency to anchor to the previous period for making decisions for the upcoming period(s), Theocharis and Harvey (2016) recommend changing the decision-making order. They find that forecast accuracy improves when forecasters start generating forecasts for the most distant future (either 5,1,2,3,4 or 5,4,3,2,1). Forecasting the most distant requires more cognitive resources than forecasting the nearest future because it changes cognitive processing from intuitive (i.e. instinct and without conscious reasoning) to deliberative which requires logical reasoning. However, this approach slows down the speed of decision making.

The information presented to the subjects can hinder or promote their trust and acceptance of systems. Leffrang and Müller (2021) find that when forecast prediction uncertainty, specifically algorithm predictive uncertainty, was (visually) presented, people were less inclined to accept suggestions from the system and perceived the time series forecasts as less valuable. In other words, when individuals became aware of the uncertainty associated with the predictions through visual representations, they were more sceptical of the suggestions and had a lower perception of the forecast's usefulness.

Conclusion: Effective interface design considers the order, framing, and format of information presentation to cater to the specific needs of tasks in different situations. The delivery system should be designed to reduce the adverse impact of cognitive limitations.

3.3. Decision aid provided

Selecting an appropriate forecasting model/algorithm is critical for the accuracy of predictions. To improve forecast quality, organisations should use appropriate software and tools that consider human needs and goals (Fildes and Petropoulos 2015). Simplicity in decision models can offer several advantages. For instance, when faced with low-complexity problems, using simpler models can lead to faster and more efficient decision-making processes. Similarly, higher process uncertainty implies simpler models that break the problem into smaller pieces. Complex models may introduce unnecessary complexity and computational burden without providing substantial improvements in decision outcomes. In situations with limited information availability, simple models are advantageous. Complex models often require large amounts of information for accurate calibration and estimation, which may not be available in data-scarce environments (Katsikopoulos, Durbach, and Stewart 2018). In fact, a review of previous research shows that unnecessary complexity increases forecasting error by approximately 27 per cent (Green and Armstrong 2015).

Humans often reject algorithmic predictions and prefer their own (or other humans') judgment, even when the algorithmic predictions are sufficiently accurate or simple (Dietvorst, Simmons, and Massey 2015; Dietvorst and Bharti 2020). This aversion increases when they receive inaccurate advice from systems (Chacon, Kausel, and Reyes 2022). Daschner and Obermaier (2022) explain that human cognitive beliefs and behaviour towards algorithms depend on the accuracy of the model. Low-performing algorithms lead to algorithm aversion, while high-performing algorithms lead to algorithm appreciation. Contrarily, Himmelstein and Budescu (2023) argue that human preference for human or algorithmic advice does not always predict the advice's use. They explain that hybrid advice is often favoured over single-sourced advice. This could be because humans believe that hybrid advice captures the strengths of both sources. Jung and Seiter (2021) explain that algorithm aversion is mitigated when humans work under time pressure because less confidence in their own choices encourages them to take the algorithmic suggestions.

To overcome algorithm aversion, researchers have explored various strategies. One effective approach is allowing humans to modify imperfect algorithms. According to Dietvorst, Simmons, and Massey (2018) and Jung and Seiter (2021), this can increase human trust and use of the algorithm. In a case study conducted by Fildes and Goodwin (2021), managers persisted with a poor-performing forecasting system because they could overwrite suggestions based on their judgment. Goodwin (2000) tests three different methods for overcoming algorithm aversion. The first method involved asking forecasters if they wanted to make a change for each forecast, with the default being no. The second method asked forecasters to input the reason for the change, while the third method involved asking forecasters to adjust existing statistical forecasts rather than generating entirely new predictions. The study concludes that the first two approaches were effective in improving the use and acceptance of algorithmic suggestions.

Forecasting accuracy results from the joint work between the system decision aid provided and the human experts (Seifert and Hadida 2013). In practice, a less accurate model prediction requires more work from human experts (Alvarado-Valencia et al. 2017). Baecke, De Baets, and Vanderheyden (2017) find that final performance improves when human predictions are integrated as a predictive variable into a forecasting model. Franses and Legerstee (2013) suggest that when the forecasting system's performance is poor, incorporating decision makers' mental models into the forecasting model is useful. Franses and Legerstee (2011) explain that incorporating the expertise of forecasters and considering their historical accuracy by assigning appropriate weights to their decisions improves the overall forecasting accuracy.

Conclusion: Model complexity should be tailored based on the careful examination of the human decision-maker's needs and cognitive capabilities. Besides, human biases that hinder trust in algorithmic advice should be considered.

4. A journey of a new system – acceptance and continued use

When designing a system, two phases of use must be considered: system acceptance and continued use (Davis 1985; Karahanna, Straub, and Chervany 1999). System acceptance refers to the extent to which humans initially accept and are willing to use a particular system (Davis 1985). The system's continued use refers to the ongoing and sustained utilisation of a system by humans over an extended period. In different phases, humans make different decisions with respect to the system, i.e. whether to adopt the system or sustain its usage. We review IS literature to understand the key factors impacting human decisions in the two phases. Table 6 summarises this literature based on the two phases of the human-system interaction journey, the research method and the relevant theories. Sections 4.1 and 4.2 discuss relevant literature on system acceptance and continued use phases, respectively.

4.1. Phase 1: system acceptance

Regardless of how intelligent the system is, without the human's willingness to use it, the system fails. Davis, Bagozzi, and Warshaw (1989) initiate the Technology Acceptance Model (TAM), in which they identify two key determinants of human attitude towards the system: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Davis defines PU as 'the degree to which a person believes that using a particular system would enhance his/her job performance' (Davis 1989, 320) and PEOU as 'the degree to which an individual believes that using a particular technology would be free from effort' (Davis 1989, 320). Although both PEOU and PU

Table 6. Summary of State-of-the-art Literature on Human-System Interaction in Information Systems.

Author	Year	Relevant Theory	Research Metod	System Phase	
				Acceptance	Continued Use
Davis et al.	1989	Technology Acceptance Model	Conceptual Model	✓	
Goodhue & Thompson	1995	Technology-to-Performance Chain	Conceptual Model	✓	
Keil et al.	1995	Technology Acceptance Model	Empirical Study	✓	✓
Venkatesh & Davis	1996	Technology Acceptance Model	Lab Experiment	✓	
Dishaw & Strong	1999	Integrated TAM/TTF Model	Conceptual Model	✓	
Agarwal & Karahanna	2000	Technology Acceptance Model	Conceptual Model	✓	
Venkatesh & Davis	2000	Technology Acceptance Model	Conceptual Model	✓	
Bhattacherjee	2001	Post Acceptance Model of IS Continuance	Conceptual Model		✓
DeLone & McLean	2003	Information System Success Model	Conceptual Model	✓	
Bhattacherjee & Premkumar	2004	Technology Acceptance Model	Conceptual Model		✓
Jasperson et al.	2005	Model of Post-Adoptive Behaviour	Conceptual Model		✓
Burton-Jones & Hubona	2006	Technology Acceptance Model	Empirical Study	✓	✓
Komiak & Benbasat	2006	Theory of Reasoned Action	Conceptual Model	✓	
Limayem et al.	2007	Post Acceptance Model of IS Continuance	Conceptual Model		✓
Larsen et al.	2009	Post Acceptance Model of IS Continuance	Conceptual Model		✓
Deng et al.	2010	Theory of Reasoned Action	Conceptual Model		✓
Rezvani et al.	2017	Post Acceptance Model of IS Continuance	Conceptual Model		✓

IS denotes Information System.

are important in shaping acceptance behaviour, PEOU is considered an antecedent of PU (Davis, Bagozzi, and Warshaw 1989). PEOU of a system could influence how humans perceive system usefulness, ultimately affecting their decision to accept or reject using the system. Before hands-on experience with the system, providing procedural information (i.e. instructions and guidelines) about the system does not impact human beliefs towards the system (Venkatesh and Davis 1996). Instead, the human's confidence in their ability to use a system (self-efficacy) influences their PEOU of the system. Keil, Beranek, and Konsynski (1995) propose a framework based on the PEOU and PU characteristics. The authors highlight the critical role of PEOU during the acceptance phase, as humans tend to resist systems that lack clarity and are difficult to learn. They suggest that improving PEOU requires improving the system's user-friendliness. Prior affinity with the system change the impact of PEOU and PU on acceptance decisions (Agarwal and Karahanna 2000). Similarly, the empirical study of Burton-Jones and Hubona (2006) shows that prior experience with a system directly increases usage.

Venkatesh and Davis (2000) extend TAM to TAM II by incorporating non-technical aspects of a system. For instance, subjective norms can influence human's PU. Subjective norms are individuals' beliefs about the expectations and opinions of others regarding the adoption and use of technology. This includes considering what colleagues, friends, or other important individuals may think about using the system. The authors explain that human attitudes towards the system are also impacted by their environment and the people they work with.

Some researchers do not explicitly distinguish between PEOU and PU. DeLone and McLean (2003) suggest that system and information qualities influence human satisfaction. The system quality is evaluated by availability, reliability, response time, etc. The information quality is evaluated by completeness, ease of understanding, and relevance. The Task-Technology Fit (TTF) model of Goodhue and Thompson (1995) claims that a better alignment between a task's requirements and the system's capabilities leads to a higher chance that the technology will be adopted and utilised effectively. Komiak and Benbasat (2006) explain two types of intention to use the technology based on its fit with human needs: intention to use as a decision aid provided and intention to use as a delegated agent. So far, we have discussed different theories separately, but integrating these models enhances our ability to explain and predict technology usage (Dishaw and Strong 1999).

Conclusion: The perceptions of usefulness and ease of use, as well as overall attitude towards a system, are shaped by a combination of system characteristics, individual differences, and social influences. PEOU is regarded as a precursor to PU throughout this dynamic interaction, highlighting the importance of user-friendly and intuitive designs in showing positive human perceptions and acceptance of technology.

4.2. Phase 2: continued use

Humans start to form their attitude towards continued use of the system after the acceptance phase (Bhattacherjee and Premkumar 2004). Burton-Jones and Hubona (2006) identify two aspects of continued use: frequency, which refers to how often a system is used over a period, and volume, which refers to how long the system is used over the same period. The authors find that positive experiences with the system impact both frequency and volume. Similarly, Bhattacherjee (2001) and Deng et al. (2010) show that a positive usage experience encourages humans to continue to use the system. This satisfaction is considered more important than human perception of the system's usefulness (Bhattacherjee 2001). Nevertheless, when the system does not prove as useful as expected, humans do not completely avoid it. Even when a system exhibits limitations, humans often tend to rely on a subset of features that they find most useful (Jasperson, Carter, and Zmud 2005). Limayem, Hirt, and Cheung (2007) show that less conscious intention is required when humans habitually use a system.

While system functionalities play a significant role in shaping human behaviour, environmental factors can also influence it. For instance, Rezvani, Khosravi, and Dong (2017) show the impact of different leadership styles (transactional vs transformational) on intrinsic and extrinsic motivation. The main difference between transformational and transactional leadership is the way leaders motivate their followers. Transformational leaders inspire and empower subordinates, while transactional leaders focus on maintaining control and offering rewards for desired performance. The authors observe that distinct leadership styles result in diverse behaviours concerning the same system. Larsen, Sørebø, and Sørebø (2009) provide two explanations for the continued use intention. The first explanation, the work system-centric, explains that humans who perceive the actual system as aligned with their work requirements tend to utilise a wider range of its functionalities, which leads to a stronger intention to continue using the system. The second explanation, satisfaction-based, explains that human satisfaction with the system is influenced by the degree to which the system meets human's initial expectations, which contributes to a strong intention to continue using the system.

Keil, Beranek, and Konsynski (1995) explain that PU becomes more important than PEOU in the continued use phase. The authors explain that while POEU attracts humans initially, the system functionalities are the important determinant of continued use. Systems with high PEOU but low PU appear attractive firsthand but have limited long-term viability. They explain that to improve the PU of the system, its functionalities should be improved. The authors conclude that successful systems should find a balance between PEOU and PU.

Conclusion: During the continued use phase, the focus shifts towards the PU. Consequently, the functionality of the system becomes crucial in determining sustained use. When the system has limitations, habit leads to reliance on the limited functionalities of the system.

5. Future research in production planning: a research agenda

In Section 2, we reviewed PP research and found limited literature on the interactions between human planners and PP systems. In Section 3, we reviewed the forecasting literature to learn about human limitations and capabilities when their decisions are supported by forecasting systems. We categorise the literature in Sections 2 and 3 based on the Zmud (1979) system elements and human factors. For example, Dietvorst and Bharti (2020) explain how algorithm aversion relates to humans' diminishing sensitivity to errors in uncertain domains. We categorise this paper under *decision aid provided* and human *cognitive limitations*.

Our review of PP and forecasting literature provides a good understanding of human limitations and capabilities related to different system elements but not yet in relation to the system phases. In Section 4, by reviewing IS literature, we introduce two phases of the journey of a new system: system acceptance and continued use. For example, we conclude that the algorithm aversion explained by Dietvorst and Bharti (2020) often occurs during the early interactions between humans and systems. We suggest that researchers and practitioners address algorithm aversion during the *system acceptance* phase rather than the continued use phase.

In this section, we introduce a two-phase × three-element matrix to provide guidelines for human-centred PP system design and to highlight future research directions. In Section 5.1, we present our primary finding regarding the system acceptance phase. We then break this finding down into three secondary findings in Sections 5.1.1 through 5.1.3, each related explicitly to one of the three system elements. Section 5.2 follows a similar structure. We start with our primary finding about the continued use phase and then present three secondary findings in Sections 5.2.1 through 5.2.3 associated with each of the three system elements.

Each section starts by discussing relevant IS research to consider during specific phases of the human-system interaction journey. We then illustrate how these findings apply by presenting relevant examples from PP and forecasting studies. These examples are categorised based on the common topics they cover. Each section ends with a discussion of possible future research directions for PP. An overview of findings per system element and system journey phase is provided in Table 7. An overview of future research topics in PP per system element and system journey phase is provided in Section 6 (see Table 8).

Table 7. Findings based on Two-phase × Three-element Matrix.

Phase	Element		
	Information Received	Delivery System	Decision Aid Provided
System Acceptance	**SA**: During the system acceptance phase, the Perceived Ease of Use (PEOU) plays an important role in shaping acceptance decisions. PEOU has greater significance in the delivery system and information received than in the decision aid provided.		
	SA.1	**SA.2**	**SA.3**
	To achieve a high PEOU, the information received has to consider quality, relevance, volume, and updating frequency.	To achieve a high PEOU, the information received has to consider quality, relevance, volume, and updating frequency.	To achieve a high PEOU, decision aid provided has to prevent unnecessary complexity and provide the ability to modify.
Continued Use	**CU**: During the continued use phase, the Perceived Usefulness (PU) plays an important role in the sustained use of the system. PU has greater significance in the decision aid provided than in the information received and delivery system.		
	CU.1	**CU.2**	**CU.3**
	To achieve a high PU, information received has to consider planners' cognitive limitations and capabilities.	To achieve a high PU, the delivery system has to consider planners' cognitive limitations.	To achieve a high PU, the decision aid provided has to consider humans in the loop.

5.1. System acceptance

In the system acceptance phase, Perceived Ease of Use (PEOU) is the primary factor influencing planners' acceptance decisions (Davis 1989). PEOU has to be considered in the system elements while designing a system (Keil, Beranek, and Konsynski 1995). The information received and the delivery system are the two essential elements of PEOU. The decision aid provided does not directly influence the PEOU (Agarwal and Karahanna 2000; Venkatesh and Davis 1996).

> Finding SA: During the system acceptance phase, the Perceived Ease of Use (PEOU) plays an important role in shaping acceptance decisions. PEOU has greater significance in the delivery system and information received than in the decision aid provided.

5.1.1. Information received

The quality and nature of the information that the planners receive during the acceptance phase influence their perception of the system (DeLone and McLean 2003). Clear, concise, and relevant information that aligns with the planners' needs and expectations enhances their understanding and confidence in using the system. Providing information tailored to specific tasks and responsibilities stimulates planners' sense of familiarity and usability, promoting acceptance (Goodhue and Thompson 1995).

> Finding SA.1: To achieve a high PEOU, information received has to consider quality, relevance, volume, and updating frequency.

5.1.1.1. Information received quality. When the available information is limited or not sufficiently accurate, we refer to it as poor information quality. Human intervention becomes crucial when poor-quality information is provided (Fildes and Petropoulos 2015). In these situations, human planners must rely on past experiences and draw analogies to fill the gaps (Lee et al. 2007). Because planners habitually overvalue the information they possess (Arnold 2018; Tong, Feiler, and Larrick 2018), when the information provided is limited, planners compensate for this by making (unnecessary) adjustments to the system suggestions (Fransoo and Wiers 2008). Similarly, framing information in a complex way leads to noisy interpretations and unnecessary adjustments (Feiler and Tong 2022).

5.1.1.2. Information received relevance. The information given to planners should be relevant to the goal (Webby, O'Connor, and Edmundson 2005). For example, if the goal is to educate planners, providing detailed descriptions is important; however, if the goal is to assist planners' decision-making, detailed information can cause confusion (Parikh, Fazlollahi, and Verma 2001). The relevance of information differs for different industries. For example, in industries where trends change quickly, historical information may not be relevant for forecasting demand (Seifert et al. 2015). In addition, the effectiveness of relevant information can differ for different individuals (Letmathe and Zielinski 2016). For instance, financial information regarding performance may be more effective for some individuals. (Goodwin, Gönül, and Önkal 2019).

5.1.1.3. Information received volume & updating frequency. Human planners have limited cognitive capacity to process large volumes of information (Webby, O'Connor, and Edmundson 2005). When a system provides planners with excessive information, they tend to obtain the initial impression that the system is burdensome. Distinguishing noise from the provided information can efficiently reduce the information volume (Satopää et al. 2021). For example, historical information can be deemed noise in the fashion industry, where trends change rapidly (Seifert et al. 2015). The information update frequency has to be compatible with the planners' cognitive capacity. When the information updates are too frequent, planners will suffer from information overload cognitive fatigue, leading to a vicious circle of errors and poor performance (Haeussler et al. 2021).

5.1.1.4. Future research directions. There are at least three directions for future research that can enhance PEOU for the information received. First, behavioural studies through lab and field experiments or empirical studies through case studies can examine which types of poor-quality information can or cannot be compensated by the planners' intuition and analogy from past experiences. Second, empirical studies through case studies and interview data can identify the relevant information to planners, e.g. capacity, delivery time, etc. Third, behavioural studies can examine what volume and updating frequency of system information does not overwhelm planners. Field and lab experiments or empirical studies through interviews can be used to determine a plausible update frequency that keeps a balance between providing timely information and avoiding unnecessary interventions. In other application areas, Bolton and Katok (2008) and Lurie and Swaminathan (2009) have studied similar topics, offering potential avenues for further research in PP.

5.1.2. Delivery system

The delivery system connects the system to the humans. Delivery system transparency and clarity are both important for the system acceptance phase (Keil, Beranek, and Konsynski 1995). Presenting the underlying model in an easy way facilitates acceptance of a system (DeLone and McLean 2003).

> Finding SA.2: To achieve a high PEOU, the delivery system has to consider effective and transparent presentations.

5.1.2.1. Presentation format in the delivery system. The delivery system should present information in an effective way. Generally, visuals perform better than complex textual information in reducing the cognitive load (Brolin, Thorvald, and Case 2017; Schock et al. 2010). The efficiency of using visuals depends on the goal. For instance, tabular presentation is more effective than figures for presenting untrended data (Harvey and Bolger 1996). However, graphical information can better highlight patterns in the trended data. Therefore, choosing an effective way to present the information is crucial (Yahouni et al. 2018).

5.1.2.2. Transparency in the delivery system. Transparency is crucial to prevent misunderstandings and to ensure accurate interpretations of the system's state and Key Performance Indicators (KPIs) (Bendul 2019; Bendul and Knollman 2016). Visualising the result of modifying algorithm constraints is an example of transparency. If the delivery system provides planners with a visual tool, such as a drag and drop, to preview the outcome of their proposed modification, the system becomes more understandable. While transparency is essential, excessive transparency has unintended negative consequences. For instance, when uncertainties in system-generated predictions are openly presented to planners, it generates unnecessary concerns about system capabilities (Leffrang and Müller 2021). This leads to a loss of trust in the system, as planners feel unsure about the reliability of the information provided (Dietvorst, Simmons, and Massey 2015).

5.1.2.3. Future research directions. There are at least two avenues for future research to enhance PEOU through the delivery system. First, behavioural studies through lab and field experiments or empirical studies through case studies can investigate whether different presentation formats, such as figures, tables, and textual information, impact planners' decision-making speed and performance differently. For instance, researchers can explore whether, through figures, humans can deal with more volume and/or updating frequency. Second, behavioural studies through lab experiments and empirical studies through interviews can assess the optimal level of transparency without causing concerns about system capabilities. Recent studies in other application areas have indicated that excessive transparency may give humans the false impression that they fully understand complex system reasoning, leading to overconfidence (DeStefano et al. 2022). Research within the realm of PP could define the right level of transparency to make sophisticated systems understandable without adverse effects.

5.1.3. Decision aid provided

During the acceptance phase, decision aid provided plays a relatively minor role because planners are mainly influenced by the information received and the delivery system. Nevertheless, decision aid provided should be designed to provide valuable support, be learnt easily, and help humans build confidence to use the system (Goodhue and Thompson 1995). Unnecessary complexity in the algorithm indirectly harms acceptance decisions. Human intention to have an active role and use a system as a decision aid provided (compared to a delegated agent) is impacted by the fit between system and task (Goodhue and Thompson 1995; Komiak and Benbasat 2006).

> Finding SA.3: To achieve a high PEOU, decision aid provided has to prevent unnecessary complexity and provide the ability to modify.

5.1.3.1. Decision aid provided complexity.

Human aversion towards algorithmic suggestions is a commonly observed phenomenon (Dietvorst, Simmons, and Massey 2015; Dietvorst and Bharti 2020). The algorithm's complexity leads to algorithm aversion (Himmelstein and Budescu 2023). Algorithms (and their complexity) should align with the specific needs of the planners (Wiendahl et al. 2005) and their tasks (Fildes and Petropoulos 2015). Unnecessary complexity leads to errors and harms the human's trust in the system (Green and Armstrong 2015). Additionally, complex models that rely on large amounts of information may not perform well when insufficient information is available (Katsikopoulos, Durbach, and Stewart 2018). In such cases, complexity leads to inaccuracies, which further increase planners' aversion towards the algorithms (Chacon, Kausel, and Reyes 2022; Daschner and Obermaier 2022).

5.1.3.2. Decision aid provided ability to modify.

Humans' overconfidence in their solutions contributes to their aversion towards algorithms (Zoryk-Schalla, Fransoo, and de Kok 2004). However, when individuals are given a sense of control over the system's suggestions, such as the ability to modify the suggestions, their aversion towards algorithms decreases (Dietvorst, Simmons, and Massey 2018; Goodwin 2000; Jung and Seiter 2021). The ability to modify the system allows the human to use the system as a tool that complements and enhances their decision-making limitations. As a result, they may quickly develop trust in the system.

5.1.3.3. Future research directions.

Future research might be able to confirm the minor role of the decision aid provided in the acceptance phase. We suggest researchers focus on the other two system elements during the acceptance phase. The decision aid provided should be the focus of the continued use phase; see Section 5.2.3.

5.2. Continued use

A system's Perceived Usefulness (PU) influences planners' sustained system usage after the acceptance phase. In the continued use phase, PU is formed and constantly evaluated against the actual usefulness of the system (Keil, Beranek, and Konsynski 1995). Misalignment between PU and actual usefulness reduces system usage (Larsen, Sørebø, and Sørebø 2009). When the system is more useful than the PU, satisfaction increases (Bhattacherjee 2001; Deng et al. 2010), and the usage in terms of both frequency and magnitude increases accordingly (Burton-Jones and Hubona 2006). However, usage decreases when the actual usefulness is less than the PU. In this case, humans who have accepted the system may still stick to using limited functionalities of the system (Jasperson, Carter, and Zmud 2005) because of the habit (Limayem, Hirt, and Cheung 2007). The PU has to be considered throughout the three elements of system design (Keil, Beranek, and Konsynski 1995). The PU is extremely important in the element of decision aid provided, as the decision aid provided determines solution quality.

> Finding CU: During the continued use phase, Perceived Usefulness (PU) plays an important role in the sustained use of the system. PU has greater significance in the decision aid provided than in the information received and delivery system.

5.2.1. Information received

Information Received has to consider human cognitive capabilities and limitations. When the information neglects human factors, it impacts human performance negatively. Planners continuously assess the actual usefulness of the information they receive to improve their decisions (Keil, Beranek, and Konsynski 1995). Less useful information leads to dissatisfaction and triggers unnecessary human interventions (Bhattacherjee 2001; Deng et al. 2010). The alignment among the information received, planners' cognitive capabilities, and task requirements increases planners' satisfaction, which leads to continued use.

> Finding CU.1: To achieve a high PU, information received has to consider planners' cognitive limitations and capabilities.

5.2.1.1. Planners' cognitive limitations.

When planners interact with the system, their cognitive biases and thinking patterns play a role (Arnold 2018; Wiers and de Kok 2017). For example, humans anchor on available information and undervalue unknown information (Tong, Feiler, and Larrick 2018). Nevertheless, providing an overload of information and frequent updates harms decision-making accuracy (Feiler and Tong 2022; Haeussler et al. 2021; Satopää et al. 2021; Webby, O'Connor, and Edmundson 2005). Therefore, providing the right volume of information contributes to the perception of the system's usefulness (Goodwin, Gönül, and Önkal 2019; Parikh, Fazlollahi, and Verma 2001).

5.2.1.2. Planners' cognitive capabilities. Planners' cognitive capabilities can compensate for missing or poor-quality information in a system (Fildes and Petropoulos 2015). Planners can make analogies from their experiences that can compensate for the missing information (Lee et al. 2007). Their information processing capabilities, such as prioritising useful information, help them identify valuable content in extensive datasets (Vijayakumar et al. 2022). Besides, humans can consolidate the information generated by different models or agents and make conclusions (Hernes and Bytniewski 2017).

5.2.1.3. Future research directions. At least two directions for future research can enhance PU for the information received. First, behavioural studies through lab and field experiments or empirical studies through case studies can identify behavioural biases due to cognitive limitations when information lacks simplicity (quality, relevance, volume, and updating frequency). Recent studies in other application areas have studied similar topics. For example, researchers can explore planners' anchoring effects when receiving irrelevant information, i.e. Yasseri and Reher (2022). Second, researchers can explore what information deficiencies planners' information processing capabilities can compensate for. For example, Robey and Taggart (1982) find that when information is missing, humans can still rely on their intuitions to make good decisions.

5.2.2. Delivery system

During the continued use phase, the emphasis shifts from the perception of the system's simplicity to the perception of the usefulness of its functionalities (Keil, Beranek, and Konsynski 1995). Systems with limited functionality cause human dissatisfaction (Jasperson, Carter, and Zmud 2005). The delivery system should consider human cognitive limitations, improving their satisfaction to promote continued use.

> Finding CU.2: To achieve a high PU, the delivery system has to consider planners' cognitive limitations.

5.2.2.1. Planners' cognitive limitations. Although the underlying model predominantly determines the PU of a system, information presentation and interface indirectly influence PU. A well-designed interface that effectively conveys its intended message needs to consider cognitive limitations. For instance, planners can be biased towards the recent updates they receive (Theocharis, Smith, and Harvey 2019). The system can mitigate this bias by letting planners make decisions starting from the most distant future period (Theocharis and Harvey 2016). Kusev et al. (2018) find that presenting events sequentially improves accuracy in forecasting, as it considers relevant events for decision-making. Yahouni et al. (2018) show that real-time disruptions can help planners, but it might not work when disruptions occur too frequently. Visual presentations can help planners make fast and high-quality decisions (Brolin, Thorvald, and Case 2017; Schock et al. 2010). Nevertheless, visual presentations are not suitable for displaying untrended information as they can lead to overreactions in decisions (Harvey and Bolger 1996). The visuals should be relevant to the task and its objectives (Stowasser 2006).

5.2.2.2. Future research directions. Several research directions can be pursued to enhance PU for the delivery system. For instance, behavioural studies through lab or field experiments or empirical studies through case studies can examine how to use visuals to mitigate planners' bias. Similarly, empirical studies can assess which types of visuals are relevant in a specific PP context. Relevant visuals can differ in variant PP contexts. In other application areas, researchers such as Benbasat and Dexter (1985), Lalomia and Coovert (1987), and Mousavi, Low, and Sweller (1995) have investigated similar topics, offering potential avenues for further research in PP.

5.2.3. Decision aid provided

During the continued use phase, the decision aid provided plays a key role in shaping the quality of solutions. The decision aid provided directly impacts the planners' experience with the system (Keil, Beranek, and Konsynski 1995). Positive usage experiences increase planners' satisfaction and encourage them to continue using the system (Bhattacherjee 2001; Deng et al. 2010; Larsen, Sørebø, and Sørebø 2009). Conversely, when the decision aid provided does not coordinate with planners well, satisfaction decreases (Jasperson, Carter, and Zmud 2005), and planners might utilise a limited set of system functionalities out of habit (Limayem, Hirt, and Cheung 2007).

> Finding CU.3: To achieve a high PU, the decision aid provided has to consider humans in the loop.

5.2.3.1. Human in the loop. PP performance is a result of the collective effort of the system and the planners (Moscoso, Fransoo, and Fischer 2010; Seifert and Hadida 2013). Planners can recognise whether a system is performing well or poorly (Baecke, De Baets, and Vanderheyden 2017). Nevertheless, they do not entirely abandon those poorly performing systems (Fildes and Goodwin 2021); instead, they rely on limited functionalities of systems because of habit, environmental factors and social norms. When systems are less accurate, more human intervention can compensate for such system limitations

(Alvarado-Valencia et al. 2017; Franses and Legerstee 2013), and thus planners' adjustments become more important. To make systems functional and effective, incorporating human cognitive capabilities is important (Merten, Hütt, and Uygun 2022). For example, algorithms that provide soft and hard constraints facilitate planners' understanding of which constraints cannot be violated while making ad hoc adjustments to the systems (Silva 2009). Algorithms can help planners' decisions. For instance, digital twins speed up planners' decisions by providing real-time information and simulations (Graessler and Pöhler 2017; Rožanec et al. 2022). Wiers and de Kok (2017) explain that humans are the main decision-makers for complex tasks, while routine tasks can be completely automated. However, the design of the decision aid provided should strike a balance between human involvement and system autonomy. Human intervention can be limited when the systems perform well (Franses and Legerstee 2011; Oberc et al. 2018). Ultimately, this collaborative approach maximises the overall performance and efficiency of the combined human-system interaction.

5.2.3.2. Future research directions. At least two directions for future research can enhance PU for the decision aid provided. First, lab and field experiments and case studies can assess the PP performance while planners are using different systems in terms of the decision aid provided. For instance, the decision aid provided can differ in terms of solution accuracy. Within PP, a limited body of research examines planners' decisions and performance while they are using different systems. In other application areas, Kahr et al. (2023), Leffrang, Bösch, and Müller (2023), Yin, Wortman Vaughan, and Wallach (2019), and Yu et al. (2017) have conducted studies on the impact of system accuracy on trust and performance. Second, researchers can analyse planners' cognitive capabilities that can be used in algorithms. Using such a behaviour-driven approach, algorithms can efficiently focus on the most relevant variables and select the most relevant datasets, improving the quality of the decision aid provided. Besides, researchers can investigate the optimal weighting of human judgment versus system suggestions to improve overall performance.

6. Discussion and conclusion

Behavioural Production Planning (PP) lacks comprehensive knowledge about human-system interaction. Researchers in PP have been developing sophisticated algorithms to deal with uncertainty (Mula et al. 2006) but have paid little attention to humans' cognitive limitations and capabilities. Most of the systems adopted by practitioners lack fundamental functionalities to assist them in performing the PP task (Graves 2011), which in turn leads to frequent and high-magnitude human interventions (Fransoo and Wiers 2008). In reviewing PP systems, Guzman, Andres, and Poler (2022) highlight the need for future researchers to concentrate on the social, economic, and environmental characteristics. Donohue, Özer, and Zheng (2020) call for research to understand human-system interaction in operations research as it provides a rich problem context. We respond to this call for action in this paper.

Table 7 summarises our theory-driven findings that serve as guidelines for designing a human-centred PP system. We propose that during the system acceptance phase, human behaviour towards the system is mainly impacted by its Perceived Ease of Use (PEOU). PEOU can be improved through the delivery system and information received. Perceived Usefulness (PU) becomes crucial for deciding whether to continue using the system during the continued use phase. PU is mainly influenced by the decision aid provided. Table 8 summarises our collective understanding of different streams of literature and translates them into future research questions in PP per system element and system journey phase. In Section 5, we explain the future research directions and the methods that we find relevant per system element. The choice of research method, however, depends on the question itself. Our approach is meant to inspire researchers to start their studies.

When systems are useful, people can still use them ineffectively. They can under-rely on the system when the system generates errors. System neglect theory explains people who focus on immediate system errors can form negative attitudes towards using the systems (Massey and Wu 2005). People can also over-rely on a system if they trust it too much. For example, a system that is designed for a highly uncertain environment includes high safety stock levels. People can over-rely on the system by accepting a high safety-stock level even when the situation becomes less uncertain.

The design of human-centred systems must account for other factors. Incentives can impact human-system interaction in two forms. One form is alignment between the system and humans. Misalignment of incentives between humans and the system can result in biased decisions (Oliva and Watson 2009). For example, a system that emphasises service levels may recommend increasing stock, which conflicts with reducing costs. Another form of incentive is the human incentive for performing well. For example, a bonus system can incentivise human planners to perform well to have less inventory costs or a high service level. The monetary-relevant incentive

Table 8. Agenda for Future Research in Production Planning per System Element and System Journey Phase.

		System Element			Human Factor		System Phase	
Future Research Question	Research Metod	Information Received	Delivery System	Decision Aid Provided	Limitations	Capabilities	Acceptance	Continued Use
Which information quality deficits can be compensated by planners' capabilities?	Lab & Field Experiment, Case Study	✓				✓	✓	
Which information is relevant to planners taking context into account?	Case Study & Interview	✓			✓		✓	
Which volume and update frequency does not overwhelm planners?	Lab & Field Experiment, Interview	✓			✓		✓	
What presentation format can improve planners' decision-making speed?	Lab & Field Experiment, Case Study		✓		✓		✓	
Which level of transparency does encourage planners' trust in system capabilities?	Lab Experiment, Interview		✓		✓		✓	
What are the planners' cognitive limitations when information lacks simplicity?	Lab & Field Experiment, Case Study	✓			✓			✓
What are the planners' capabilities when information lacks simplicity?	Lab & Field Experiment, Case Study	✓				✓		✓
How can the presentation format incorporate planners' cognitive limitations?	Lab & Field Experiment, Case Study		✓		✓			✓
How does the solution accuracy impact planners' performance?	Lab & Field Experiment, Case Study			✓	✓			✓
How can we incorporate planners' cognitive capabilities into the solution?	Lab & Field Experiment, Case Study			✓		✓		✓

can also contribute to the human planners' motivation to adapt themselves to use a new system. Thus, human performance is shaped by the broader ecosystem (Gino and Pisano 2008; Schweitzer and Cachon 2000).

Our purpose for writing this paper was to offer a drop of clarity in the complex ocean of human-system interaction in PP. We hope that our paper can be the starting step in explaining (inconsistent) results of current literature, a guideline for system designers to focus on designing human-centred systems, and a call to action for researchers to focus on the human-system interaction in PP.

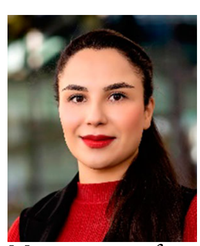
Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributors



Maryam Azani is a PhD candidate in the Operations Planning, Accounting, and Control (OPAC) Department at Eindhoven University of Technology (TU/e), Netherlands. She holds a Master's degree in Business Information Technology from the University of Twente and a Bachelor's degree in Industrial Engineering and Management from the University of Tehran. Her research focuses on behavioural factors in operations management and the design of human-centred systems to enhance performance.

Lijia Tan is an Assistant Professor specialising in Behavioural Operations Management at Eindhoven University of Technology (TU/e), Netherlands. She received her PhD in Economics from Xiamen University, China. Prior to joining TU/e, she served as an Assistant Professor at Tianjin University, China. She also served as a postdoctoral researcher at Cologne University, Germany, and TU/e. Her research focuses on human decisions in Industry 5.0, Supply Chain Management, Auctions, and Experimental Economics.

Rob Basten is an Associate Professor at Eindhoven University of Technology (TU/e), where he is primarily occupied with after-sales operations for high-tech equipment. He is especially interested in using new technologies to improve services. For example, 3D printing of spare parts on location and using condition monitoring information to perform just-in-time maintenance. He is further active in behavioural operations management, trying to understand how people can use decision support systems in such a way that they actually improve decisions and add value. Many of his research projects are interdisciplinary and are performed in cooperation with the high-tech industry.

Ton de Kok is a Full Professor at the School of Industrial Engineering at Eindhoven University of Technology and Director of CWI in Amsterdam. His research concerns the optimisation of operational business processes under uncertainty in the context of supply chain management, transportation management and production management. His work has been implemented in many different industries, ranging from transportation process industries to capital goods industries. The empirical validity of the models and their analysis has provided clear evidence of the importance of stationary stochastic models.

ORCID

Maryam Azani http://orcid.org/0000-0002-2089-3163
Lijia Tan http://orcid.org/0000-0002-7007-2515
Rob Basten http://orcid.org/0000-0003-4562-9681
Ton de Kok http://orcid.org/0000-0001-8622-8599

References

Agarwal, R., and E. Karahanna. 2000. “Time Flies When You’re Having fun: Cognitive Absorption and Beliefs About Information Technology Usage.” *MIS Quarterly* 24:665–694. https://doi.org/10.2307/3250951

Alvarado-Valencia, J., L. H. Barrero, D. Önkal, and J. T. Dennerlein. 2017. “Expertise, Credibility of System Forecasts and Integration Methods in Judgmental Demand Forecasting.” *International Journal of Forecasting* 33 (1): 298–313. https://doi.org/10.1016/j.ijforecast.2015.12.010

APICS. 2009. *APICS Operations Management Body of Knowledge Framework (OMBOK)*. Chicago, IL: APICS.

Arnold, M. G. 2018. “Combining Conscious and Unconscious Knowledge Within Human-Machine-Interfaces to Foster Sustainability with Decision-Making Concerning Production Processes.” *Journal of Cleaner Production* 179:581–592. https://doi.org/10.1016/j.jclepro.2018.01.070

Arvan, M., B. Fahimnia, M. Reisi, and E. Siemsen. 2019. “Integrating Human Judgement Into Quantitative Forecasting Methods: A Review.” *Omega* 86:237–252. https://doi.org/10.1016/j.omega.2018.07.012

Baecke, P., S. De Baets, and K. Vanderheyden. 2017. “Investigating the Added Value of Integrating Human Judgement Into Statistical Demand Forecasting Systems.” *International Journal of Production Economics* 191:85–96. https://doi.org/10.1016/j.ijpe.2017.05.016

Baumeister, R. F., and M. R. Leary. 1997. “Writing Narrative Literature Reviews.” *Review of General Psychology* 1 (3): 311–320. https://doi.org/10.1037/1089-2680.1.3.311

Benbasat, I., and A. S. Dexter. 1985. “An Experimental Evaluation of Graphical and Color-Enhanced Information Presentation.” *Management Science* 31 (11): 1348–1364. https://doi.org/10.1287/mnsc.31.11.1348

Bendul, J. 2019. “Understanding the Meaning of Human Perception and Cognitive Biases for Production Planning and Control.” *IFAC-PapersOnLine* 52 (13): 2201–2206. https://doi.org/10.1016/j.ifacol.2019.11.532

Bendul, J. C., and M. Knollman. 2016. “The Human Factor in Production Planning and Control: Considering Human Needs in Computer Aided Decision-Support Systems.” *International Journal of Manufacturing Technology and Management* 30 (5): 346–368. https://doi.org/10.1504/IJMTM.2016.078921

Bhattacherjee, A. 2001. “Understanding Information Systems Continuance: An Expectation-Confirmation Model.” *MIS Quarterly* 25:351–370. https://doi.org/10.2307/3250921

Bhattacherjee, A., and G. Premkumar. 2004. “Understanding Changes in Belief and Attitude Toward Information Technology Usage: A Theoretical Model and Longitudinal Test.” *MIS Quarterly* 28:229–254. https://doi.org/10.2307/25148634

Bolton, G. E., and E. Katok. 2008. “Learning by Doing in the Newsvendor Problem: A Laboratory Investigation of the Role of Experience and Feedback.” *Manufacturing & Service Operations Management* 10 (3): 519–538. https://doi.org/10.1287/msom.1060.0190

Boulaksil, Y., and P. H. Franses. 2009. “Experts’ Stated Behavior.” *Interfaces* 39 (2): 168–171. https://doi.org/10.1287/inte.1080.0421

Boyacı, T., C. Canyakmaz, and F. de Véricourt. 2024. “Human and Machine: The Impact of Machine Input on Decision Making Under Cognitive Limitations.” *Management Science* 70 (2): 1258–1275. https://doi.org/10.1287/mnsc.2023.4744

Brolin, A., P. Thorvald, and K. Case. 2017. “Experimental Study of Cognitive Aspects Affecting Human Performance in Manual Assembly.” *Production & Manufacturing Research* 5 (1): 141–163. https://doi.org/10.1080/21693277.2017.1374893

Burton-Jones, A., and G. S. Hubona. 2006. “The Mediation of External Variables in the Technology Acceptance Model.” *Information & Management* 43 (6): 706–717. https://doi.org/10.1016/j.im.2006.03.007

Chacon, A., E. E. Kausel, and T. Reyes. 2022. “A Longitudinal Approach for Understanding Algorithm use.” *Journal of Behavioral Decision Making*.

Christova, N. G., P. P. Groumpos, and C. D. Stylios. 2003. “Production Planning for Complex Plants Using Fuzzy Cognitive Maps.” *IFAC Proceedings Volumes* 36 (3): 81–86. https://doi.org/10.1016/S1474-6670(17)37739-X

Daniel, K. 2017. *Thinking, fast and slow*.

Daschner, S., and R. Obermaier. 2022. “Algorithm Aversion? On the Influence of Advice Accuracy on Trust in Algorithmic Advice.” *Journal of Decision Systems* 31 (sup1): 77–97. https://doi.org/10.1080/12460125.2022.2070951

Davis, F. D. 1985. *A Technology Acceptance Model for Empirically Testing new end-User Information Systems: Theory and Results*. Cambridge, MA: Massachusetts Institute of Technology.

Davis, F. D. 1989. “Perceived Usefulness, Perceived Ease of use, and User Acceptance of Information Technology.” *MIS Quarterly* 13:319–340. https://doi.org/10.2307/249008

Davis, F. D., R. P. Bagozzi, and P. R. Warshaw. 1989. “User Acceptance of Computer Technology: A Comparison of two Theoretical Models.” *Management Science* 35 (8): 982–1003. https://doi.org/10.1287/mnsc.35.8.982

DeLone, W. H., and E. R. McLean. 2003. “The DeLone and McLean Model of Information Systems Success: A ten-Year Update.” *Journal of Management Information Systems* 19 (4): 9–30. https://doi.org/10.1080/07421222.2003.11045748

Deng, L., D. E. Turner, R. Gehling, and B. Prince. 2010. “User Experience, Satisfaction, and Continual Usage Intention of IT.” *European Journal of Information Systems* 19 (1): 60–75. https://doi.org/10.1057/ejis.2009.50

DeStefano, T., K. Kellogg, M. Menietti, and L. Vendraminelli. 2022. *Why providing humans with interpretable algorithms may, counterintuitively, lead to lower decision-making performance*.

Dietvorst, B. J., and S. Bharti. 2020. “People Reject Algorithms in Uncertain Decision Domains Because They Have Diminishing Sensitivity to Forecasting Error.” *Psychological Science* 31 (10): 1302–1314. https://doi.org/10.1177/0956797620948841

Dietvorst, B. J., J. P. Simmons, and C. Massey. 2015. “Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them err.” *Journal of Experimental Psychology: General* 144 (1): 114. https://doi.org/10.1037/xge0000033

Dietvorst, B. J., J. P. Simmons, and C. Massey. 2018. “Overcoming Algorithm Aversion: People Will use Imperfect Algorithms if They Can (Even Slightly) Modify Them.” *Management Science* 64 (3): 1155–1170. https://doi.org/10.1287/mnsc.2016.2643

Dishaw, M. T., and D. M. Strong. 1999. “Extending the Technology Acceptance Model with Task–Technology fit Constructs.” *Information & Management* 36 (1): 9–21. https://doi.org/10.1016/S0378-7206(98)00101-3

Donohue, K., Ö Özer, and Y. Zheng. 2020. “Behavioral Operations: Past, Present, and Future.” *Manufacturing & Service Operations Management* 22 (1): 191–202. https://doi.org/10.1287/msom.2019.0828

Eriksson, K. M., L. Carlsson, and A. K. Olsson. 2022. “To Digitalise or not? Navigating and Merging Human-and Technology Perspectives in Production Planning and Control.” *The International Journal of Advanced Manufacturing Technology* 122 (11-12): 4365–4373. https://doi.org/10.1007/s00170-022-09874-x

Feiler, D., and J. Tong. 2022. “From Noise to Bias: Overconfidence in new Product Forecasting.” *Management Science* 68 (6): 4685–4702. https://doi.org/10.1287/mnsc.2021.4102

Fildes, R., and P. Goodwin. 2021. “Stability in the Inefficient use of Forecasting Systems: A Case Study in a Supply Chain Company.” *International Journal of Forecasting* 37 (2): 1031–1046. https://doi.org/10.1016/j.ijforecast.2020.11.004

Fildes, R., and F. Petropoulos. 2015. “Improving Forecast Quality in Practice.” *Foresight: The International Journal of Applied Forecasting* 36:5–12.

Franses, P. H., and R. Legerstee. 2011. “Combining SKU-Level Sales Forecasts from Models and Experts.” *Expert Systems with Applications* 38 (3): 2365–2370. https://doi.org/10.1016/j.eswa.2010.08.024

Franses, P. H., and R. Legerstee. 2013. “Do Statistical Forecasting Models for SKU-Level Data Benefit from Including Past Expert Knowledge?” *International Journal of Forecasting* 29 (1): 80–87. https://doi.org/10.1016/j.ijforecast.2012.05.008

Fransoo, J. C., and V. C. S. Wiers. 2008. “An Empirical Investigation of the Neglect of MRP Information by Production Planners.” *Production Planning and Control* 19 (8): 781–787. https://doi.org/10.1080/09537280802568163

Galbraith, J. 1973. *Designing Complex Organisations*. Mass: Reading.

Gino, F., and G. Pisano. 2008. “Toward a Theory of Behavioral Operations.” *Manufacturing & Service Operations Management* 10 (4): 676–691. https://doi.org/10.1287/msom.1070.0205

Goodhue, D. L., and R. L. Thompson. 1995. “Task-technology fit and Individual Performance.” *MIS Quarterly* 19:213–236. https://doi.org/10.2307/249689

Goodwin, P. 2000. “Improving the Voluntary Integration of Statistical Forecasts and Judgment.” *International Journal of Forecasting* 16 (1): 85–99. https://doi.org/10.1016/S0169-2070(99)00026-6

Goodwin, P., M. S. Gönül, and D. Önkal. 2019. “When Providing Optimistic and Pessimistic Scenarios Can be Detrimental to Judgmental Demand Forecasts and Production Decisions.” *European Journal of Operational Research* 273 (3): 992–1004. https://doi.org/10.1016/j.ejor.2018.09.033

Graessler, I., and A. Pöhler. 2017. “Integration of a Digital Twin as Human Representation in a Scheduling Procedure of a Cyber-Physical Production System.” 2017 ieee international conference on industrial engineering and engineering management (IEEM), 289–293.

Graves, S. C. 2011. “Uncertainty and Production Planning.” In *Planning Production and Inventories in the Extended Enterprise*, edited by K. G. Kempf, P. Keskinocak, and R. Uzsoy, 83–101. New York, NY: Springer.

Green, K. C., and J. S. Armstrong. 2015. “Simple Versus Complex Forecasting: The Evidence.” *Journal of Business Research* 68 (8): 1678–1685. https://doi.org/10.1016/j.jbusres.2015.03.026

Grosse, E. H., C. H. Glock, M. Y. Jaber, and W. P. Neumann. 2015. “Incorporating Human Factors in Order Picking Planning Models: Framework and Research Opportunities.” *International Journal of Production Research* 53 (3): 695–717. https://doi.org/10.1080/00207543.2014.919424

Guide Jr, V. D. R., and R. Srivastava. 2000. “A Review of Techniques for Buffering Against Uncertainty with MRP

Systems." *Production Planning & Control* 11 (3): 223–233. https://doi.org/10.1080/095372800232199

Guzman, E., B. Andres, and R. Poler. 2022. "Models and Algorithms for Production Planning, Scheduling and Sequencing Problems: A Holistic Framework and a Systematic Review." *Journal of Industrial Information Integration* 27:100287. https://doi.org/10.1016/j.jii.2021.100287

Haeussler, S., M. Stefan, M. Schneckenreither, and A. Onay. 2021. "The Lead Time Updating Trap: Analysing Human Behavior in Capacitated Supply Chains." *International Journal of Production Economics* 234:108034. https://doi.org/10.1016/j.ijpe.2021.108034

Harvey, N., and F. Bolger. 1996. "Graphs Versus Tables: Effects of Data Presentation Format on Judgemental Forecasting." *International Journal of Forecasting* 12 (1): 119–137. https://doi.org/10.1016/0169-2070(95)00634-6

Hernes, M., and A. Bytniewski. 2017. "Knowledge Integration in a Manufacturing Planning Module of a Cognitive Integrated Management Information System." Computational collective intelligence: 9th international conference, ICCCI 2017, Nicosia, Cyprus, September 27-29, 2017, proceedings, part I 9, 34–43.

Himmelstein, M., and D. V. Budescu. 2023. "Preference for Human or Algorithmic Forecasting Advice Does not Predict if and how it is Used." *Journal of Behavioral Decision Making* 36 (1): e2285. https://doi.org/10.1002/bdm.2285

Jasperson, Jon, P. E. Carter, and R. W. Zmud. 2005. "A Comprehensive Conceptualisation of Post-Adoptive Behaviors Associated with Information Technology Enabled Work Systems." *MIS Quarterly* 29:525–557. https://doi.org/10.2307/25148694

Jung, M., and M. Seiter. 2021. "Towards a Better Understanding on Mitigating Algorithm Aversion in Forecasting: An Experimental Study." *Journal of Management Control* 32 (4): 495–516. https://doi.org/10.1007/s00187-021-00326-3

Kahr, P. K., G. Rooks, M. C. Willemsen, and C. C. P. Snijders. 2023. "It Seems Smart, but It Acts Stupid: Development of Trust in AI Advice in a Repeated Legal Decision-Making Task." Proceedings of the 28th international conference on intelligent user interfaces, 528–539.

Karahanna, E., D. W. Straub, and N. L. Chervany. 1999. "Information Technology Adoption Across Time: A Cross-Sectional Comparison of pre-Adoption and Post-Adoption Beliefs." *MIS Quarterly* 23:183–213. https://doi.org/10.2307/249751

Katsikopoulos, K. V., I. N. Durbach, and T. J. Stewart. 2018. "When Should we use Simple Decision Models? A Synthesis of Various Research Strands." *Omega* 81:17–25. https://doi.org/10.1016/j.omega.2017.09.005

Keil, M., P. M. Beranek, and B. R. Konsynski. 1995. "Usefulness and Ease of use: Field Study Evidence Regarding Task Considerations." *Decision Support Systems* 13 (1): 75–91. https://doi.org/10.1016/0167-9236(94)E0032-M

Kesavan, S., and T. Kushwaha. 2020. "Field Experiment on the Profit Implications of Merchants' Discretionary Power to Override Data-Driven Decision-Making Tools." *Management Science* 66 (11): 5182–5190. https://doi.org/10.1287/mnsc.2020.3743

Khosrowabadi, N., K. Hoberg, and C. Imdahl. 2022. "Evaluating Human Behaviour in Response to AI Recommendations for Judgemental Forecasting." *European Journal of Operational Research*.

King, W. R., and B. J. Epstein. 1976. "Assessing the Value of Information." *Management Datamatics* 5 (4): 171–180.

Kocsi, B., M. M. Matonya, L. P. Pusztai, and I. Budai. 2020. "Real-time Decision-Support System for High-mix low-Volume Production Scheduling in Industry 4.0." *Processes* 8 (8): 912. https://doi.org/10.3390/pr8080912

Koh, S. C. L., and S. M. Saad. 2003. "A Holistic Approach to Diagnose Uncertainty in ERP-Controlled Manufacturing Shop Floor." *Production Planning & Control* 14 (3): 273–289. https://doi.org/10.1080/0953728031000111487

Komiak, S. Y. X., and I. Benbasat. 2006. "The Effects of Personalisation and Familiarity on Trust and Adoption of Recommendation Agents." *MIS Quarterly* 30:941–960. https://doi.org/10.2307/25148760

Kusev, P., P. Van Schaik, K. Tsaneva-Atanasova, A. Juliusson, and N. Chater. 2018. "Adaptive Anchoring Model: How Static and Dynamic Presentations of Time Series Influence Judgments and Predictions." *Cognitive Science* 42 (1): 77–102. https://doi.org/10.1111/cogs.12476

Lalomia, M. J., and M. D. Coovert. 1987. "A Comparison of Tabular and Graphical Displays in Four Problem-Solving Domains." *ACM SIGCHI Bulletin* 19 (2): 49–54. https://doi.org/10.1145/36111.1045596

Larsen, T. J., A. M. Sørebø, and Ø Sørebø. 2009. "The Role of Task-Technology fit as Users' Motivation to Continue Information System use." *Computers in Human Behavior* 25 (3): 778–784. https://doi.org/10.1016/j.chb.2009.02.006

Lauer, T., R. Welsch, S. Ramlah Abbas, and M. Henke. 2020. "Behavioral Analysis of Human-Machine Interaction in the Context of Demand Planning Decisions." Advances in artificial intelligence, software and systems engineering: proceedings of the AHFE 2019 international conference on human factors in artificial intelligence and social computing, the AHFE international conference on human factors, software, Se, 130–141.

Lauer, T., and S. Wieland. 2021. "Human-AI-Collaboration in the Context of Information Asymmetry–A Behavioral Analysis of Demand Forecasting." Advances in artificial intelligence, software and systems engineering: proceedings of the AHFE 2021 virtual conferences on human factors in software and systems engineering, artificial intelligence and social computing, and energy, July 25-29, 2021, USA, 3–13.

Lawrence, M., P. Goodwin, M. O'Connor, and D. Önkal. 2006. "Judgmental Forecasting: A Review of Progress Over the Last 25 Years." *International Journal of Forecasting* 22 (3): 493–518. https://doi.org/10.1016/j.ijforecast.2006.03.007

Lee, W. Y., P. Goodwin, R. Fildes, K. Nikolopoulos, and M. Lawrence. 2007. "Providing Support for the use of Analogies in Demand Forecasting Tasks." *International Journal of Forecasting* 23 (3): 377–390. https://doi.org/10.1016/j.ijforecast.2007.02.006

Leffrang, D., K. Bösch, and O. Müller. 2023. *Do People Recover from Algorithm Aversion? An Experimental Study of Algorithm Aversion over Time*.

Leffrang, D., and O. Müller. 2021. "Should I Follow This Model? The Effect of Uncertainty Visualisation on the Acceptance of Time Series Forecasts." *2021 IEEE Workshop on TRust and EXpertise in Visual Analytics (TREX)*, 20–26. https://doi.org/10.1109/TREX53765.2021.00009

Letmathe, P., and M. Zielinski. 2016. "Determinants of Feedback Effectiveness in Production Planning." *International*

Journal of Operations & Production Management 36 (7): 825–848. https://doi.org/10.1108/IJOPM-12-2014-0623

Limayem, M., S. G. Hirt, and C. M. K. Cheung. 2007. “How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance.” *MIS Quarterly* 31:705–737. https://doi.org/10.2307/25148817

Liu, X., L. Faes, A. U. Kale, S. K. Wagner, D. J. Fu, A. Bruynseels, T. Mahendiran, G. Moraes, M. Shamdas, and C. Kern. 2019. “A Comparison of Deep Learning Performance Against Health-Care Professionals in Detecting Diseases from Medical Imaging: A Systematic Review and Meta-Analysis.” *The Lancet Digital Health* 1 (6): e271–e297. https://doi.org/10.1016/S2589-7500(19)30123-2

Liu, C., M. Yang, and M. Wen. 2023. “Judge me on my Losers: Do Robo-Advisors Outperform Human Investors During the COVID-19 Financial Market Crash?” *Production and Operations Management* 32 (10): 3174–3192. https://doi.org/10.1111/poms.14029

Lurie, N. H., and J. M. Swaminathan. 2009. “Is Timely Information Always Better? The Effect of Feedback Frequency on Decision Making.” *Organisational Behavior and Human Decisión Processes* 108 (2): 315–329. https://doi.org/10.1016/j.obhdp.2008.05.005

MacCarthy, B. L., and J. R. Wilson. 2003. *Human Performance in Planning and Scheduling*. Boca Raton, FL: CRC Press.

Massey, C., and G. Wu. 2005. “Detecting Regime Shifts: The Causes of Under-and Overreaction.” *Management Science* 51 (6): 932–947.

McKay, K. N., and V. C. S. Wiers. 2006. “The Human Factor in Planning and Scheduling.” In *Handbook of Production Scheduling*, edited by J. W. Herrmann, 23–57. New York, NY: Springer.

Merten, D. C., M.-T. Hütt, and Y. Uygun. 2022. “A Network Analysis of Decision Strategies of Human Experts in Steel Manufacturing.” *Computers & Industrial Engineering* 168:108120. https://doi.org/10.1016/j.cie.2022.108120

Moscoso, P. G., J. C. Fransoo, and D. Fischer. 2010. “An Empirical Study on Reducing Planning Instability in Hierarchical Planning Systems.” *Production Planning and Control* 21 (4): 413–426. https://doi.org/10.1080/09537280903454172

Mousavi, S. Y., R. Low, and J. Sweller. 1995. “Reducing Cognitive Load by Mixing Auditory and Visual Presentation Modes.” *Journal of Educational Psychology* 87 (2): 319. https://doi.org/10.1037/0022-0663.87.2.319

Mula, J., R. Poler, J. P. García-Sabater, and F. C. Lario. 2006. “Models for Production Planning Under Uncertainty: A Review.” *International Journal of Production Economics* 103 (1): 271–285. https://doi.org/10.1016/j.ijpe.2005.09.001

Oberc, H., M. Reuter, M. Wannöffel, and B. Kuhlenkötter. 2018. “Development of a Learning Factory Concept to Train Participants Regarding Digital and Human Centered Decision Support.” *Procedia Manufacturing* 23:165–170. https://doi.org/10.1016/j.promfg.2018.04.011

Oliva, R., and N. Watson. 2009. “Managing Functional Biases in Organisational Forecasts: A Case Study of Consensus Forecasting in Supply Chain Planning.” *Production and Operations Management* 18 (2): 138–151. https://doi.org/10.1111/j.1937-5956.2009.01003.x

Paisley, W. J. 1968. “Information Needs and Uses.” *Annual Review of Information Science and Technology* 3 (1): 1–30.

Parikh, M., B. Fazlollahi, and S. Verma. 2001. “The Effectiveness of Decisional Guidance: An Empirical Evaluation.” *Decision Sciences* 32 (2): 303–332. https://doi.org/10.1111/j.1540-5915.2001.tb00962.x

Perera, H. N., J. Hurley, B. Fahimnia, and M. Reisi. 2019. “The Human Factor in Supply Chain Forecasting: A Systematic Review.” *European Journal of Operational Research* 274 (2): 574–600. https://doi.org/10.1016/j.ejor.2018.10.028

Quiroga, B. F., B. Moritz, and A. Ovchinnikov. 2019. “Behavioral Ordering, Competition and Profits: An Experimental Investigation.” *Production and Operations Management* 28 (9): 2242–2258. https://doi.org/10.1111/poms.13032

Rezvani, A., P. Khosravi, and L. Dong. 2017. “Motivating Users Toward Continued Usage of Information Systems: Self-Determination Theory Perspective.” *Computers in Human Behavior* 76:263–275. https://doi.org/10.1016/j.chb.2017.07.032

Robey, D., and W. Taggart. 1982. “Human Information Processing in Information and Decision Support Systems.” *MiS Quarterly* 6:61–73. https://doi.org/10.2307/249283

Rožanec, J. M., J. Lu, J. Rupnik, M. Škrjanc, D. Mladenić, B. Fortuna, X. Zheng, and D. Kiritsis. 2022. “Actionable Cognitive Twins for Decision Making in Manufacturing.” *International Journal of Production Research* 60 (2): 452–478. https://doi.org/10.1080/00207543.2021.2002967

Satopää, V. A., M. Salikhov, P. E. Tetlock, and B. Mellers. 2021. “Bias, Information, Noise: The BIN Model of Forecasting.” *Management Science* 67 (12): 7599–7618. https://doi.org/10.1287/mnsc.2020.3882

Schock, A., B. Ryan, J. Wilson, T. Clarke, and S. Sharples. 2010. “Visual Scenario Analysis: Understanding Human Factors of Planning in Rail Engineering.” *Production Planning and Control* 21 (4): 386–398. https://doi.org/10.1080/09537280903454123

Schweitzer, M. E., and G. P. Cachon. 2000. “Decision Bias in the Newsvendor Problem with a Known Demand Distribution: Experimental Evidence.” *Management Science* 46 (3): 404–420. https://doi.org/10.1287/mnsc.46.3.404.12070

Seifert, M., and A. L. Hadida. 2013. “On the Relative Importance of Linear Model and Human Judge (s) in Combined Forecasting.” *Organisational Behavior and Human Decision Processes* 120 (1): 24–36. https://doi.org/10.1016/j.obhdp.2012.08.003

Seifert, M., E. Siemsen, A. L. Hadida, and A. B. Eisingerich. 2015. “Effective Judgmental Forecasting in the Context of Fashion Products.” *Journal of Operations Management* 36 (1): 33–45. https://doi.org/10.1016/j.jom.2015.02.001

Silva, C. 2009. “Combining ad hoc Decision-Making Behaviour with Formal Planning and Scheduling Rules: A Case Study in the Synthetic Fibre Production Industry.” *Production Planning and Control* 20 (7): 636–648. https://doi.org/10.1080/09537280903034321

Silver, E. A., D. F. Pyke, and D. J. Thomas. 2016. “Inventory and Production Management in Supply Chains.” *Inventory and Production Management in Supply Chains*, https://doi.org/10.1201/9781315374406.

Stowasser, S. 2006. “Computer-supported Visualisation of Distributed Production Area Information.” *Production Planning & Control* 17 (2): 202–213. https://doi.org/10.1080/09537280500224176

Theocharis, Z., and N. Harvey. 2016. “Order Effects in Judgmental Forecasting.” *International Journal of Forecasting* 32 (1): 44–60. https://doi.org/10.1016/j.ijforecast.2015.01.007

Theocharis, Z., L. A. Smith, and N. Harvey. 2019. "The Influence of Graphical Format on Judgmental Forecasting Accuracy: Lines Versus Points." *Futures & Foresight Science* 1 (1): e7. https://doi.org/10.1002/ffo2.7

Tong, J., D. Feiler, and R. Larrick. 2018. "A Behavioral Remedy for the Censorship Bias." *Production and Operations Management* 27 (4): 624–643. https://doi.org/10.1111/poms.12823

Tranfield, D., D. Denyer, and P. Smart. 2003. "Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review." *British Journal of Management* 14 (3): 207–222. https://doi.org/10.1111/1467-8551.00375

Van Donselaar, K. H., V. Gaur, T. Van Woensel, R. A. C. M. Broekmeulen, and J. C. Fransoo. 2010. "Ordering Behavior in Retail Stores and Implications for Automated Replenishment." *Management Science* 56 (5): 766–784. https://doi.org/10.1287/mnsc.1090.1141

Venkatesh, V., and F. D. Davis. 1996. "A Model of the Antecedents of Perceived Ease of use: Development and Test." *Decision Sciences* 27 (3): 451–481. https://doi.org/10.1111/j.1540-5915.1996.tb01822.x

Venkatesh, V., and F. D. Davis. 2000. "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies." *Management Science* 46 (2): 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Vijayakumar, V., F. Sgarbossa, W. P. Neumann, and A. Sobhani. 2022. "Framework for Incorporating Human Factors Into Production and Logistics Systems." *International Journal of Production Research* 60 (2): 402–419. https://doi.org/10.1080/00207543.2021.1983225

Webby, R., M. O'Connor, and B. Edmundson. 2005. "Forecasting Support Systems for the Incorporation of Event Information: An Empirical Investigation." *International Journal of Forecasting* 21 (3): 411–423. https://doi.org/10.1016/j.ijforecast.2004.10.005

Wiendahl, H.-P., G. von Cieminski, C. Begemann, and R. Nickel. 2005. "Human Factors in Production Planning and Control: How to Change Potential Stumbling Blocks Into Reliable Actors." Integrating human aspects in production management: IFIP TC5/WG5. 7 proceedings of the international conference on human aspects in production management 5–9 October 2003, karlsruhe, Germany, 113–125.

Wiers, V. C. S., and A. T. G. de Kok. 2017. *Designing, Selecting, Implementing and Using aps Systems*. Cham: Springer.

Wolfswinkel, J. F., E. Furtmueller, and C. P. M. Wilderom. 2013. "Using Grounded Theory as a Method for Rigorously Reviewing Literature." *European Journal of Information Systems* 22 (1): 45–55. https://doi.org/10.1057/ejis.2011.51

Wong, P.-M., and C.-K. Chui. 2022. "Cognitive Engine for Augmented Human Decision-Making in Manufacturing Process Control." *Journal of Manufacturing Systems* 65:115–129. https://doi.org/10.1016/j.jmsy.2022.09.007

Yahouni, Z., N. Mebarki, F. Belkadi, A. Shahzad, and A. Bernard. 2018. "Human-machine Cooperation in Planning and Scheduling: A Case Study on an Unstable Environment." *European Journal of Industrial Engineering* 12 (6): 757–780. https://doi.org/10.1504/EJIE.2018.096388

Yasseri, T., and J. Reher. 2022. "Fooled by Facts: Quantifying Anchoring Bias Through a Large-Scale Experiment." *Journal of Computational Social Science* 5 (1): 1001–1021. https://doi.org/10.1007/s42001-021-00158-0

Yin, M., J. Wortman Vaughan, and H. Wallach. 2019. "Understanding the Effect of Accuracy on Trust in Machine Learning Models." Proceedings of the 2019 Chi conference on human factors in computing systems, 1–12.

Yu, K., S. Berkovsky, R. Taib, D. Conway, J. Zhou, and F. Chen. 2017. "User Trust Dynamics: An Investigation Driven by Differences in System Performance." Proceedings of the 22nd international conference on intelligent user interfaces, 307–317.

Zmud, R. W. 1979. "Individual Differences and MIS Success: A Review of the Empirical Literature." *Management Science* 25 (10): 966–979. https://doi.org/10.1287/mnsc.25.10.966

Zoryk-Schalla, A. J., J. C. Fransoo, and T. G. de Kok. 2004. "Modeling the Planning Process in Advanced Planning Systems." *Information & Management* 42 (1): 75–87. https://doi.org/10.1016/j.im.2003.06.005