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A behavioral perspective on visualization in manufacturing and operations management: a review, framework, and research agenda

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Abstract

Visualizations are ubiquitous in today's manufacturing operations, whether in the form of time series, scatter plots, flow charts, or dashboards. Managers, engineers, and shop-floor workers use visualizations to understand and act on production data for monitoring, problem solving, decision making, and strategy development. How we present the information we need influences our actions and behaviors. Therefore, we systematically review and analyze the current literature in manufacturing and operations management on visualizations and their relationship to behavioral operations in terms of social, cognitive, and emotional benefits as well as resulting performance improvements of production systems. Through content analysis of 64 papers from 1997 to 2023 across eight operational contexts and types of visualizations, we find typical purposes, benefits, and pitfalls where behavioral mechanisms are prevalent. Visualizations are used to facilitate knowledge explanation and sharing for improved communication and collaboration, or to reduce cognitive load and mental cost for increased quality and resource efficiency in task execution. The results are synthesized in an integrative framework that explains the links between visualizations and operations through their common behavioral mechanisms. We propose eight directions and map concrete hypotheses for future research in this area to promote the targeted development, deployment, and evaluation of visualizations in manufacturing considering behavioral and operational performance factors. Our study contributes to the emerging literature on visualizations in operations management, provides an overview and guidance for further efforts in this area, and helps practitioners reflect on and improve their design and use of visualizations, thereby advancing their management toolbox.

Keywords Information and data visualization · Manufacturing · Behavioral operations management · Systematic literature review · Content analysis

1 Introduction

The role of visualizations as an efficient and effective part of companies' information and decision support systems (DSS) is becoming increasingly important as Industry 4.0 (I4.0), the Industrial Internet of Things (IIoT), or even Industry 5.0 (I5.0) place data at the core of modern production to achieve operational excellence (Breque et al. 2021; Huchzermeier

et al. 2022; Kagermann et al. 2013; Xu et al. 2021). Visualizations help to harness this complex, multidimensional information by aggregating, displaying, and communicating it in a meaningful way to the respective decision maker. The proliferation of open-source visualization tools such as D3.js, Apache ECharts, or Google Charts (Jin 2022), and easy-to-use, scalable visualization software such as Tableau, allows anyone in an organization to quickly create their own visualizations tailored to their specific needs.

Because of visualization's strengths in facilitating our cognitive processing of information and providing us with faster insights into complex, multifaceted, and abstract matters (Keim et al. 2010; Ware 2012), poorly designed visualizations can just as easily lead us to incorrect conclusions (Bresciani and Eppler 2015). This can lead to unintended, counterproductive, or even costly behaviors and decisions

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in manufacturing and operations management (Basole et al. 2021; Bendoly 2016).

To further investigate the potential influences of visualizations on such behavioral processes, and subsequently their impact on the performance of production systems, we apply the method of a systematic literature review (SLR). This allows us to integrate knowledge from both the behavioral operations management (BOM) and information visualization (InfoVis) research areas by identifying the state of the art in the literature, uncovering corresponding behavioral and visual mechanisms that influence operations, revealing potential research gaps, and proposing a research agenda (Denyer and Tranfield 2009; Snyder 2019).

Our SLR aims to make theoretical and practical contributions by exploring and identifying patterns between both bodies of knowledge through their integration, and by deriving new (testable) propositions (Durach et al. 2021; Snyder 2019). The findings can also help management practitioners identify appropriate interventions, i.e., visualizations, that will serve their purposes in specific contexts (Denyer et al. 2008). Our research approach thus aligns well with previous calls to investigate how information systems and technologies can help people make better decisions (Fahimnia et al. 2019), and contributes to the emerging discourse on the effective design and use of visualizations in production and operations management (P&OM; Basole et al. 2021; Bendoly 2016) and BOM in particular (Perera et al. 2020), industry (EFFRA 2016), and management in general (Meyer et al. 2013).

We will focus on the study of social, cognitive, and emotional (hereafter also summarized as behavioral) mechanisms that play a role in both BOM and InfoVis, with roots in behavioral psychology (Cui and Wu 2018; Bendoly et al. 2010; Eppler and Platts 2009 with reference to Bürgi and Roos 2003; Roos et al. 2004). Table 1 presents examples of such behavioral biases, i.e., deviations from rational behavior, in operations management, as well as the corresponding benefits and pitfalls of visualizations, which are further described in the foundations section (Section 2).

In addition, we are interested in the impact of visualizations on the performance of production systems or parts thereof, i.e., the outcomes, and how metrics of success or failure of visual interventions are defined and measured at the level of operational systems, the individual, or technical aspects such as computation and rendering.

Previous reviews on visualization in manufacturing and P&OM, such as those by Lou et al. (2020), Ramanujan et al. (2017), Sackett et al. (2006), Wang et al. (2022), and Zhou et al. (2019), lacked a specific investigation of the connection between visualization and behavioral operations (Appendix: Table 18). These reviews focused on different contexts, such as manufacturing sequence management, sustainable lifecycle design, smart manufacturing, supply chain decision making,

and manufacturing multimedia data. While their objectives were similar—to evaluate the applications and potential of visualizations in their respective contexts and to pave the way for future research—Ramanujan et al. (2017), Zhou et al. (2019), Lou et al. (2020), and Wang et al. (2022) showed different levels of rigor in their reviews, especially in terms of transparency. In a notable exception, Sackett et al. (2006) was the only review to explicitly outline the theoretical underpinnings prior to conducting their research, specifically citing scheduling and cognitive fit theory (Vessey 1991).

Unlike the previous reviews, the current work combines the rigor of a SLR with the theoretical underpinnings of behavioral psychology to focus specifically on the cognitive, social, and emotional relationships between visualizations and manufacturing operations. To the best of our knowledge, this is the first study to address the following research questions (RQs).

RQ 1: How are visualizations treated in the current production and operations management literature in general?

RQ 1.1: To what extent are behavioral mechanisms related to operations and visualizations addressed?

RQ 1.2: How are the effects of these mechanisms measured?

RQ 2: What are the research gaps and potentials of visualizations in production and operations management with respect to behavioral mechanisms?

This article is an evolution of the Lindner et al. (2022a) conference paper and includes significant extensions and improvements to all its parts. The remainder of this review article is organized as follows. First, in Sections 2.1 and 2.2, we describe the theoretical foundations of P&OM and behavioral operations, as well as the rationale of information and data visualization upon which we have built our investigations, before presenting our conceptual framework for analyzing the literature in Section 2.3. Section 3 describes the methods of SLR and content analysis that we used. The results of our analyses are presented in Section 4 (RQs 1–1.2), before they are synthesized, discussed, and further research and development venues are proposed (Section 5; RQ 2). Section 6 concludes our study of the existing body of knowledge in P&OM and BOM and highlights our contributions to the field.

2 Foundations

In this section, we present the theoretical foundations on which our research is grounded. These are both the fields of behavioral operations (management) and InfoVis, and

Table 1 Exemplary behavioral biases in operations management and potential influences by visualizations

Behavioral biases and mechanisms	Potential benefits and pitfalls of visualizations
<i>Cognitive biases^a</i>	<i>Cognitive benefits and pitfalls</i>
Bounded rationality—Individuals are limited in their rational decision making, using heuristics over accurate judgments due to cognitive effort (Conlisk 1996). We observe bounded rationality in various operations such as inventory management, service operations, or capacity management.	Facilitate elicitation and synthesis—Using visual means helps to increase the capacity of human input channels. Visualizations help solve complex problems by condensing information and identifying patterns (Eppler and Platts 2009). Overload, redundancy, over-complexity, difficult to understand—Visualizations that contain too many elements or are too complex may result in too much cognitive effort for the viewer to decode (Bresciani and Eppler 2015).
Cognitive reflection—People with high cognitive reflection have a higher tendency not to follow intuitive but incorrect “gut” feelings, but to think further analytically about a correct answer (Kahneman 2012). This mechanism plays a role, e.g., in newsvendor decisions or production management tasks.	Over-/under-reliable appearance—Highly elaborated visualizations may provoke less critical analysis than preliminary sketches (Bresciani and Eppler 2015).
Judgement bias—Especially under uncertainty, people tend to make overly optimistic or pessimistic decisions (Tversky and Kahneman 1974). This can be the case in inventory and revenue management or forecasting.	Better, more exhaustive comparisons—Visualizations enhance our working memory and allow us to store and compare multiple options and alternatives more easily (Eppler and Platts 2009). Over-simplification, ambiguity—Leaving out essential information in visualizations, such as uncertainty or probabilities, as well as ambiguous representations can lead to biased conclusions (Bresciani and Eppler 2015).
Reference dependency—Mental anchors influence our decisions by referring to inadequate or latest information instead of the most appropriate information as the basis for our next decisions (Tversky and Kahneman 1974). Examples of this behavior can be found in inventory management and forecasting.	(Wrong) salience—Focusing on the (wrong) visual means can reinforce (wrong) mental anchors (Bresciani and Eppler 2015).
Cognitive dissonance—Receiving conflicting information that may not be consistent with one's beliefs can lead to undesirable behavior. This can be the case in service operations or quality management.	Channel thinking—Visualizations can channel thinking in a particular (undesirable) way (Bresciani and Eppler 2015).
Availability bias—Recently acquired information that is easy to recall is overrated in its importance for future judgments (Tversky and Kahneman 1973, 1974). This can occur in service operations, for example.	Easier recall and sequencing—Visualizations help recall information more effectively than verbal recall and support sequencing of different streams (Eppler and Platts 2009). Recency effect—The meaning of a visualization depends also on the viewer's previous exposure to information or alike (Bresciani and Eppler 2015).
<i>Social mechanisms and challenges</i>	<i>Social benefits and pitfalls</i>
Communication—Communication between two parties, such as in product design, and thus social investment, may influence the other party's acceptance of proposed revisions (Fahimnia et al. 2019).	Supporting mutual understanding—Graphic metaphors can explain basic assumptions and ensure mutual understanding (Eppler and Platts 2009).
Coordination—Supply chain coordination may be affected by the degree of information sharing (Fahimnia et al. 2019).	Tracking, showing interdependencies—Visualizations can help to establish reference points for mutual coordination and alignment (Eppler and Platts 2009).
Culture—Differing cultures may affect buyer-supplier relationships in supply chain management (Donohue et al. 2018; Fahimnia et al. 2019).	Cultural and cross-cultural differences—Because meanings and perceptions of symbols and colors are not universal, visualizations can be misinterpreted (Bresciani and Eppler 2015).
Power—Hierarchies, power balance, fairness and trust levels between buyers and suppliers play a critical role in supply chain management (Donohue et al. 2018; Fahimnia et al. 2019).	Hierarchy, exercise of power, and rhythms of freezing and unfreezing—The political use of visuals in collaborative settings can lead to inequalities. In addition, a particular perspective may be presented too rigorously without allowing for other perspectives (Bresciani and Eppler 2015).
Social embeddedness—In product design or technology development social embeddedness and autonomy are relevant to consider (Fahimnia et al. 2019).	Integrating different perspectives—Visualization can reduce the dominance of certain participants and reveal areas of agreement and disagreement (Eppler and Platts 2009).
<i>Emotional mechanisms and challenges</i>	<i>Emotional benefits and pitfalls</i>

Table 1 (continued)

Behavioral biases and mechanisms	Potential benefits and pitfalls of visualizations
Emotional states affect information processing, planning, individual judgments in decision making, and even groupthink, such as in product development and project management (Grushka-Cockayne et al. 2018).	Engage, inspire, and persuade—Images and visuals stimulate people's imagination and creativity, evoke positive emotions, and lend themselves to persuasive presentations (Eppler and Platts 2009). Personal likes and dislikes—Certain unpleasant visuals or images can cause negative emotions or even illness. This also relates to personal likes and dislikes, as well as prior experience with certain visualizations (Bresciani and Eppler 2015).

^a Adapted from Fahimnia et al. (2019) and Donohue et al. (2018).

especially their overlaps concerning cognitive, social, and emotional mechanisms (Table 1). In the following, the underlying theories, models, research approaches, and applications of both fields will be presented in greater detail, before eventually presenting our conceptual framework for the analysis, integrating both fields.

2.1 Behavioral operations

Operations management (OM) in general is concerned with the design, management, and improvement of operating systems and processes. This applies to various fields like healthcare, military, and supply chain (SC) in the wider, or production operations in the narrow sense. Manufacturing or production management (PM) in specific is especially dealing with manufacturing operations like scheduling and task assignment, but also product design, production control, and manufacturing engineering. I.e., manufacturing operations are themselves at the intersection of management and technics (Hopp and Spearman 2011).

BOM is a multidisciplinary branch of OM that explicitly considers the effects of human non-hyper-rational behavior and decision-making on operating systems and process performance in these contexts, influenced by cognitive biases, social preferences, and cultural norms (Fahimnia et al. 2019 referencing Croson et al. 2013; Gino and Pisano 2008; Katsikopoulos and Gigerenzer 2013; Loch and Wu 2007). Most of its theories and models are based on cognitive and social psychology as well as behavioral economics research (Bendoly et al. 2010; Donohue et al. 2018).

Major theories, concepts, and observed regularities concerning behavioral operations in SCM are, e.g. (Table 1; Fahimnia et al. 2019): non-rational behavior due to risk attitudes of individuals (e.g., risk neutrality, aversion, or seeking) with informing theories like prospect or expected utility theory, anchoring and insufficient (order) adjustment (AIA) behavior (Schweitzer and Cachon 2000), non-rational behavior due to reference dependency, pull-to-center (PtC) effects, bounded rationality, overconfidence, judgment bias, mental accounting, the degree of system 1/system 2 thinking

(cognitive reflection), mental accounting, cognitive dissonance, regret, the endowment effect, cognitive appraisal, and others.

Behavioral regularities (i.e., deviations from rationality) have been observed in OM and SC management (SCM) in contexts like inventory management (esp. in the newsvendor problem and as causes for the bullwhip effect), contracting, buyer-supplier relationships, information sharing, logistics management, but also specifically in procurement and auctions, service operations, project management, revenue management, forecasting, quality management, capacity management, new product management, production management, process improvement, or risk management (Table 1; Donohue et al. 2018; Fahimnia et al. 2019).

Prominent research methods to investigate behavioral reactions, actions, or intentions (Donohue and Schultz 2018) are analytical models, lab and field experiments, empirical studies using secondary data, surveys, or case study research, as well as systems dynamics analyses (Bendoly et al. 2010; Donohue and Schultz 2018).

2.2 Information visualization

InfoVis deals with the technical process of creating certain views and interaction techniques for a given type of data (Keim et al. 2008). The newer term visual analytics goes beyond the pure representation of data or information and includes human factors, such as perception or cognition, and advanced data analysis algorithms to enhance overall decision-making. It combines scientific visualization and InfoVis with the disciplines of data management, data analysis, perception, and cognition, as well as human-computer interaction (Keim et al. 2008; Ware 2012). Typical low-level activities executed with the help of visualizations are, e.g., finding anomalies, clusters, or correlations, computing derived values, characterizing distributions, finding an extremum, filtering, ordering, determining a range, or retrieving a value (Amar et al. 2005). On a more aggregate level, these activities can also be characterized as being exploratory or confirmatory (e.g., Sackett et al. 2006).

Perceptual and cognitive aspects in visual analytics relate to how we perceive different objects, forms, colors, and changes, how we look for information, process it, make sense of what we see, and eventually store the information in our memory (Keim et al. 2010). Prominent theories in this regard are, e.g., the dual-coding theory, which states that verbal and visual information are processed separately by humans and thus, both in combination are more effective (Paivio 1969). Also, Gestalt psychology explains how humans automatically (try to) attach order and sense to what is visually perceived by similarity, proximity, connection, enclosure, completion, and continuity (Wong 2010a, b).

Such research from psychology is beneficial to design visualizations in ways that visual processing and eventually reasoning are optimized, ideally also tackling the cognitive biases of the analysts (Keim et al. 2010). Therefore, also guidelines and principles exist to apply Gestalt principles (Wong 2010a, b) efficiently and effectively, visual building blocks (Keck et al. 2020), visual variables, semiotics, and encodings (Keck et al. 2020; MacEachren et al. 2012; Moody 2009), or best-practices (Moody 2009).

However, the general evaluation of visual analytics is still overly complex and may encompass, e.g., quantitative, qualitative, combined, or informal methods (Keim et al. 2008) to assess how the visualization meets the requirements of the intended purpose. Usually, efficiency, effectiveness, and user satisfaction are assessed as quality criteria of visual analytics. Therefore, aspects such as task completion time or error rate are measured. However, as visual analytics is highly exploratory and its outcome is knowledge generation and insights in non-deterministic settings, it becomes also important to assess its impact on the human reasoning process (Keim et al. 2010). In this case, qualitative approaches like observations and interviews might be more suitable (Keim et al. 2010).

Van Wijk (2005) has made an effort to assess the value of visualizations by enumerating the degrees of freedom of a prospective decision-maker before and after using a visualization as “just claiming that a visualization gives insight is not enough, if we want to offer additional value”. The economic value can then also be assessed, e.g., by calculating the monetary value of the time saved or the consequences of a possible wrong decision (van Wijk 2005).

Management and business literature specifically concerned with the design, application, and/or impact of visualizations as well as their underlying cognitive and other mechanisms are, e.g., Meyer et al. (2013) for organization management, Täuscher and Abdelkafi (2017) as well as Malinova and Mendling (2021) for business (process) models, resp. information systems, or Lurie and Mason (2007) for marketing. For specific problems and decisions in OM, the targeted and elaborated design and use of visualizations

for decision-making is still in its infancy (Bendoly 2016). An exception might be the case of visual management as part of the lean management concept (e.g., Bateman et al. 2016; Greif 1991).

2.3 Conceptual framework

Bringing together the previous research and theoretical foundations, we conceptualized an integrative framework as a starting point to guide our further investigations on InfoVis in P&OM (Table 2). To this end, we combined and adapted the existing frameworks specifically related to visualization in management by Eppler and Platts (2009) and Bendoly (2016) and integrated them with the overall assessment model of the management literature by Denyer and Tranfield (2009; Section 3) to identify context-relevant management interventions and outcomes. In addition, we enhanced this overall nested framework by incorporating both the behavioral and visual mechanisms perspectives inherent in operations management visualizations.

While Denyer and Tranfield's (2009) CIMO (context, intervention, mechanism, outcome) logic generally serves as a guideline for extracting and systematizing relevant information from the literature, the adaptation of Eppler and Platts' (2009) conceptual framework for visual strategizing to the operations context allows us to further specify the characteristic situations (when; Table 2) in which specific content, i.e., different types of information (what), such as data, opinions, options, plans, actions, physical properties, or abstract constructs, are visualized. Furthermore, Eppler and Platts (2009) propose to distinguish the intended benefits of using visualizations (why) in different situations, namely, to elicit or synthesize information, to compare

Table 2 Conceptual framework integrating behavioral and visual mechanisms in manufacturing and operations management

Operations cluster		#1	#2	...	#n
Framework					
Context (C) ^a	When? ^b
	Content (what?) ^b
Intervention (I) ^a	Benefit (why?) ^b	Semiotic framework ^c
	Method (how?) ^b	
Mechanism (M) ^a	Behavioral ^d	
	Visual ^d	
Outcome (O) ^a	
Classification ^d	

^aCIMO logic for systematic reviews of management literature (Denyer and Tranfield 2009). ^bConceptual framework for visual strategizing (Eppler and Platts 2009). ^cSemiotic framework for management data visualization (Bendoly 2016). ^dThis paper's conceptual framework contribution

different perspectives, to depict sequences and interdependencies, or to motivate and track people's actions.

To capture the why and how of the visualizations as interventions (I; Table 2), we additionally use Bendoly's (2016) adaptation of Peirce's classic semiotic framework to management data visualization (Bendoly 2016, referencing Peirce 1931–35, 1958). In this way, we can show the intended purpose to be conveyed by the visualization, the underlying relationships to be represented, and the concrete properties of the final representation, each at three different levels (Bendoly 2016).

In addition, we specifically include behavioral (Table 1) and visual mechanisms (M) as a dimension of our integrated conceptual framework (Table 2) as our original contribution with this study. With visual mechanisms, we target additional aspects of the cognitive, social, and emotional mechanisms of visualizations, such as the perception and processing of visual information. This approach allows us to focus specifically on the behavioral perspective when reviewing the literature, while integrating both the BOM and InfoVis fields and explaining the relationships between them through their psychological links. Finally, we intend to classify the characteristics of visualizations in specific operations clusters that we identify in the literature.

3 Methods

To answer our research questions, we chose to conduct an SLR with content analysis. Compared to a conventional review as in Sackett et al. (2006), the advantage of an SLR is its replicable, scientific, and transparent process to minimize the selection bias (Perera et al. 2020; Tranfield et al. 2003). Its main purposes are the summary of the existent knowledge on a topic and thus represent the starting point for novel research in this area (Seuring et al. 2005). In addition, content analysis proves to be a suitable tool for an SLR by analyzing documents in a structured, transparent, and reproducible way (Seuring et al. 2005). Concerning management and organization studies Denyer et al. (2008) and Denyer and Tranfield (2009) suggest following the CIMO (context, intervention, mechanism, outcome) logic to conduct an SLR resulting in propositions for research and development. In our case, this approach

helps to identify within the selected literature why and how visualizations work in certain manufacturing contexts. After formulating the review questions of interest using the CIMO logic, we are further following the proposed five-step review process of Denyer and Tranfield (2009): question formulation, locating studies, study selection and evaluation, analysis, and synthesis, reporting and using the results. These steps are described in detail in the following sections by locating, selecting, and evaluating relevant research papers, before analyzing and synthesizing them. Finally, the results are reported, discussed, and used for research propositions (Fig. 1).

3.1 Systematic literature review

Our SLR does not claim to exhaustively define but to scope and overview the literature (Snyder 2019) concerning visualizations in manufacturing and (behavioral) operations management's ranked outlets. To the best of our knowledge, the literature has not yet been investigated in the light of visualizations and both manufacturing (technical) and operations management—let alone behavioral operations. Therefore, this SLR is meant to be a first effort to oversee the field, proposing further streams of investigations to follow as well as practical implications for peers (Durach et al. 2021; Snyder 2019). Fig. 2 depicts the overall literature collection process which will be further detailed in the following sections, and which resulted in 64 publications included in our analysis and synthesis.

3.1.1 Review questions and search process

As we are interested in the usage of visualizations in P&OM, the main databases and outlets we are investigating stem from the community of (general) economics, business (informatics), and management research. Following the CIMO logic of Denyer and Tranfield (2009) for systematically reviewing management literature, we oriented our review questions to our RQs, focusing on manufacturing contexts (C), the visualizations applied as interventions (I), underlying (human) mechanisms (M) and the outcomes (O):

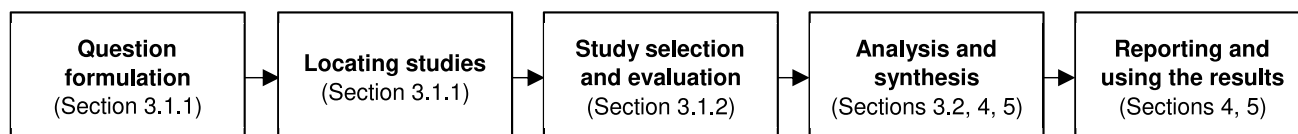


Fig. 1 Review process (based on Denyer and Tranfield 2009)

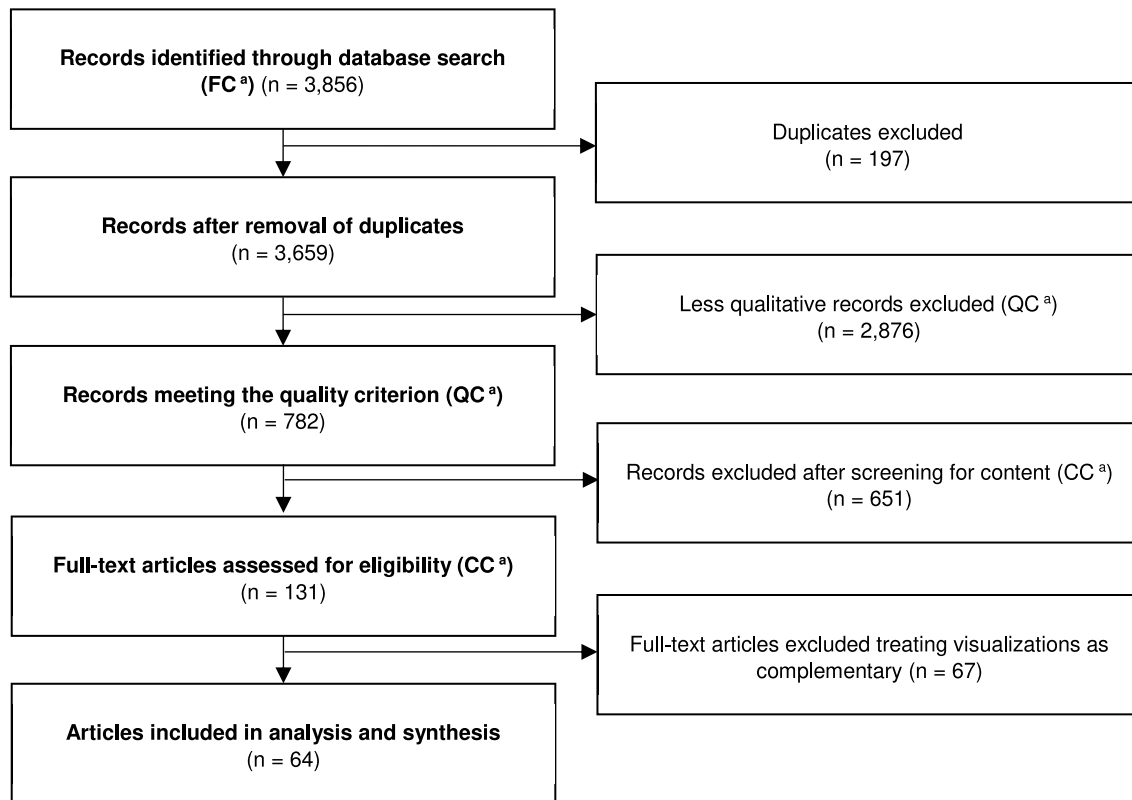


Fig. 2 Flowchart of the literature collection process (adapted from Moher et al. 2009). ^a Applied Formal (FC), Quality (QC) and Content (CC) Criteria (Section 3.1.2; Table 4)

- In which operational contexts of manufacturing companies (C) are what kind of visualizations (I) applied and/or investigated?
 - What perceptual, behavioral, or other human factors (C) are considered when designing or applying visualizations (I)?
- What are outcomes (O) of visualizations (I) in operational contexts (C)?
 - Which mechanisms (M) lead to which outcomes (O) and why?
 - How are underlying mechanisms (M) assessed and the outcomes (O) measured?

We searched academic databases applying the following search phrase including Boolean operators to address both fields of interest (Denyer and Tranfield 2009): (production OR manufacturing) AND (visualization OR visualisation). These broad search terms were intentionally chosen in line with the goal of our study, as an initial attempt to get an overview of the field (Snyder 2019), which also addresses our RQ1 (Section 1). More specific search terms did not yield significantly more or qualitatively better results at the time of this work.

The initial search was performed in August 2020 complemented by additional ones in September 2021 and October 2023 within the following databases: Web of Science Core Collection (Clarivate™), Scopus (Elsevier B.V.) and ABI/INFORM® Global (ProQuest; Table 3). It includes articles published or made available online (including articles in press) until October 2023. Since we are interested in the fundamental relationships between BOM and InfoVis, which are linked by their behavioral mechanisms, we considered it legitimate to include literature published several years ago. Although visualization technologies are advancing rapidly, and visualization techniques reported in older publications may be outdated, we believe that the underlying psychological foundations are still valid when applied to today.

Further filters that were applied during the database search—where possible—should make sure to only take into consideration articles published in peer-reviewed scholarly journals written in English, as this is the universal language in international research (Drubin and Kellogg 2012). This means as well, that book chapters, conference proceedings, reports, and practitioners' journals were excluded. This first search phase, therefore, resulted in 3,856 papers and 3,659 ones after discarding redundant articles from the whole text corpus due to duplications.

Table 3 Characteristics and results of the literature search in academic databases

Search phrase	Database	Date	Search Fields	Filters	Results
(production OR manufacturing) AND (visualization OR visualisation)	Web of Science Core Collection (Clarivate™)	August 2020	Topic (searches title, abstract, author keywords, and Keywords Plus)	Document types: article or review Languages: English Timespan: all years (1956–2020)	752
		September 2021		...Timespan: 2020–2021	124
	Scopus ^a (Elsevier B.V.)	October 2023	Title, abstract, keyword (TITLE-ABS-KEY)	Document types: article or review Language: English Source type: journal Date of publication: > August 2021	1,787
		August 2020	Anywhere except full text—NOFT	Limit to: peer reviewed Source type: scholarly journals Document type: article Language: English Publication date: all dates	973
	ABI/INFORM® (ProQuest)	September 2021		...Publication date: 2020–2021	75
		October 2023		...Publication date: September 2021–2023	145

^a Due to access restrictions, the Scopus database was used instead of the Web of Science Core Collection in October 2023

3.1.2 Literature selection and evaluation

To ensure the review of high-quality contributions, papers that were further considered for analysis must have been published in an outlet that is part of at least the top three tiers of either one of the following rankings: the German VHB-JOURQUAL3 (2015), the British AJG (2018), or the French CNRS (2019). This resulted in 782 papers. Finally,

irrelevant papers were removed from the text corpus after reading the abstracts and further applying the content criteria for the inclusion respectively exclusion of papers. Therefore, papers were only included, if the development, improvement, application, and/or evaluation of any kind of visualization and/or methods to produce visualizations in any context of discrete manufacturing operations was addressed sufficiently to be able to make an academic judgment upon its

Table 4 Inclusion (and exclusion) criteria for the analysis of the literature

Criterion (C)	Description	Rationale
Formal (FC)	The article is written in English and published in a peer-reviewed scholarly journal.	This inclusion criterion aims at ensuring a minimum scientific standard and outreach—a peer-review process, full research papers, and written in the English language. At the same time, this means that proceedings papers, editorials, abstracts, book chapters, and other document types than articles are excluded.
Quality (QC)	The article was published in a scientific journal ranked either in VHB-JOURQUAL3 (2015) with a minimum of C/D, in AJG (2018) with a minimum of 2, or in CNRS (2019) with a minimum of 3.	This criterion helps to include only papers with a minimum quality standard in and with relation to the field of production and operations management.
Content (CC)	The article sufficiently addresses the development, improvement, application, and/or evaluation of any kind of visualization in any context of discrete manufacturing operations.	To sufficiently synthesize the state-of-the-art literature in production management that is treating visualizations, to identify research gaps, and potential future directions, it is necessary to include solely papers that are dealing with the related aspects in certain depth. This means, for example, the mere mentioning of visualizations and/or production contexts would be insufficient for the inclusion of the respective paper.

classification (Table 4). This resulted in 131 contributions of which 64 are treating visualizations exclusively (49%), while the remaining 67 articles are investigating visualizations as a complementary part of a broader problem-solving or decision-making support system (51%).

3.2 Content analysis

The literature corpus was analyzed using the method of content analysis. In a first attempt, we clustered the literature according to operational contexts and types of visualizations along several dimensions and categories. Second, we analyzed the literature within these clusters in depth according to our conceptual framework to explain the behavioral relationships between visualizations and operations (Table 2).

First, structural dimensions and respective analytical categories of the literature review were derived from the initial conceptual framework (Section 2.3; Table 2) and further specified using literature on visualizations, visual analytics, as well as production and operations management in general (deductively; Lindner et al. 2022b) and the outcome of this literature review itself (inductively; Mayring 2019; Table 5; Fig. 3). In this way, we inductively derived and added a category for visualizations in educational and training contexts for manufacturing, and one for any overarching or supporting activities concerning manufacturing operations like general management of manufacturing organizations, strategizing, project management, or respective offered services. Additionally, we included a category for visualizations used in any context of Computer-Aided X (CAX), e.g., computer-aided design (CAD), planning (CAP), manufacturing (CAM), and the like. The AR or VR type of display device or interface (technology) was added as well due to the increasing number of papers that deals with these technologies for visualizations. And finally, the number of publications from the engineering domain required adding “engineering approach” as a distinct methods category for classification.

Overall, the investigated structural dimensions are (Table 5): operational context, type of visualization (Fig. 3), behavioral (social, cognitive, emotional) mechanisms as well as performance indicators and measurements, and used research approach (methods). In addition to the content-wise dimensions, we further assessed the bibliographic meta-information of the papers. The articles were categorized and classified by the first two authors based on academic judgment. To enhance the power of the literature review, the assignments of both authors were considered complementary. I.e., publications could also be assigned to several categories of one dimension. Thus, no potential valuable contribution of a publication should be missed. Only if there

were objections by one of the researchers, the respective assignments were discussed and an agreement reached.

In a subsequent second step, we applied the integrative conceptual framework for visualizations in manufacturing and operations management (Table 2) to analyze the literature in more detail and to explain relationships between behavioral and visual mechanisms. The transparent reporting of the whole process in this Section 3, as well as the explication of the inclusion (and exclusion) criteria (Table 4) and the analytical dimensions and categories (Table 5; Fig. 3), allows the traceability of decisions and judgments made during the content analysis and ensures the validity as well as reliability of the content analysis as a measurement for the quality of the applied method (Wankmüller and Reiner 2020).

4 Findings

In this section, we first present a bibliographic overview of the literature analyzed, including the monitoring of the publications over time, the research methods used, authors and citations to characterize our sample of the body of literature. We then present and describe in more detail the research on visualization along the eight identified operational context clusters more in detail: product development and design, manufacturing layout, production planning, production monitoring and control, shop floor management, supply chain management, education and training, and entrepreneurship, organization, project management, and service orientation. In line with our RQs 1–1.2 (Section 1) and research methods (Section 3), the representative literature along each operational cluster is presented and described in terms of the specific purpose (context) for which certain visualizations (interventions) are studied and the role played by social, cognitive, and emotional aspects (mechanism/outcome) as well as performance measures (outcome) according to our conceptual framework (Table 2).

4.1 Bibliographic overview

The earliest identified publication on visualization in P&OM is from Bengtsson et al. (1997), investigating differences in the perceived usefulness of paper and computer-designed workplace depictions to assess planning and ergonomics aspects. The latest assessed articles are from 2023 ($n = 7$). From 1997 to 2005 on average one article per year on the topic was published, whereas from 2006 to 2014 and from 2015 to 2021 (in September) it was two articles on average, while a local peak in publications was in 2006 with six ones (Fig. 4). While the range of the number of publications per year was very different

Table 5 Description of the analytical dimensions and categories of the content analysis

Dimension	Category	Description
Operational Context	Product Development	Product Development and Design: Aspects related to a new product, technology, or process development like designing, development, or innovation
	Manufacturing Layout	Manufacturing Layout and Workplace Design: Including (physical) facility layout and planning as well as workplace design (ergonomics)
	Production Planning	Production Planning and Data Envelopment Analysis: Planning and (virtual) designing of manufacturing sequences, flow, capacities, scheduling, order releases, resource allocation to meet different customer orders, etc.
	Production Control	Production Monitoring and Control: Monitoring and control of production processes, performances, and deviations to take corrective actions.
	Shop Floor Management	Shop Floor and Visual Management: Management of shop floor workers and activities, worker assignment, visual management, continuous improvement processes, and others
	Supply Chain Management	Activities related to the management (design, coordination, etc.) of complete supply and value chains, including several entities and operations from procurement over production and logistics to distribution
	Education and Training ^a	Manufacturing, (industrial) engineering, and production management education activities as well as worker training and (further) education
	Organizational and Strategic ^{1a}	Entrepreneurship, Organization, Project Management and Service-Orientation (Other): General category, including all other general aspects related to e.g., entrepreneurship, organization, project management, or service-orientation.
Type of Visualization	Images and Figurative	Concrete/realistic (images) and figurative (iconic/signs), pictorial representation of real-world (tangible) objects
	Graphs and Networks	(Formalized) representations using nodes and edges (mathematical notation, based on graph and network theory)
	Flow Charts	(Formalized) representation of flows and process steps, e.g., using boxes and arrows (non-mathematical notation)
	Hierarchies and Tables	(Hierarchical) data represented as table(s), treemaps, or other hierarchies (Parush et al. 2007)
	2-Dimensional	Conventional data charts with two axes or dimensions (2D coordinate system)
	3-Dimensional	Conventional data charts with three axes or dimensions (3D coordinate system)
	Computer-Aided X ^a	Visualizations of properties (proportions, dimensions) of real objects ("digital twin") using computer graphics, e.g., computer-aided design (CAD), computer-aided manufacturing (CAM), computer-aided planning (CAP), etc.
	Augmented and Virtual Reality ^a	Visualizations using augmented or virtual reality technology
Behavioral Factor / Performance	Social	Social aspects and challenges considered or addressed by the visualization, e.g., communication or coordination (Eppler and Platts 2009)
	Cognitive	Cognitive aspects and challenges considered or addressed by the visualization, e.g., information overload (Eppler and Platts 2009)
	Emotional	Emotional aspects and challenges considered or addressed by the visualization, e.g., motivation or engagement (Eppler and Platts 2009); also: user acceptance, trust, perceived usefulness, etc.
	Performance	Human performance aspects and challenges considered or addressed by the visualization (technology), e.g., human decision-making quality, errors, search and find performance, cost savings, time savings due to visual decision-making, etc.; but also: usability and ergonomics
Research Approach	Case Study	Investigation of real-world phenomena in practice at a company or similar, most of the time heavily using interview studies
	Action-based Research	Designing and testing (researching) a solution/intervention in (social) practice; not necessarily a tangible (technical) result

Table 5 (continued)

Dimension	Category	Description
	Engineering Approach ^a	Technical improvement of existing artifacts or designing of new ones, following a clear structure of problem statement, requirement analysis, and (prototype) development, resulting in tangible results (hard-/software), meeting a specific need
	Experiment	Field or laboratory behavioral experiments
	Conceptual Approach	Development and/or proposition of a concept that has not yet been implemented and/or tested
	Literature Review	(Systematic) reviews of a body of literature that go beyond reviews of the literature at the beginning of usual research papers in scope and depth; systematic literature reviews usually include protocols for search and analysis of the literature
	Analytical Model	Analytical/mathematical models describing a phenomenon (and a solution)
	Survey	(Semi-)standardized survey/questionnaire studies
	Computational (Experiment)	Experimental designs as used in (computer) simulations or linear programming

^aCategory derived inductively, i.e., from the analyzed literature itself

during the first two periods (1997–2005 and 2006–2014) (between 0 and 3 and 0 and 6, respectively), it could be perceived that the output of publications per year became more stable from 2015 to 2020 (between 2 and 4) and even increased slightly from 2021 onwards. However, it is difficult to derive and interpret any trends, as this is highly dependent on the length of the periods under consideration.

The top three outlets for publishing the research were *Computers in Industry* ($n = 15$), *International Journal on Production Research* ($n = 10$), and *Computers & Industrial Engineering* ($n = 5$), closely followed by *Sustainability* ($n = 4$). The other journals published two or fewer articles (Fig. 5).

Concerning research methods, by far engineering approaches ($n = 25$) have been used the most often, followed by case study research (mostly interview-based; $n = 18$) and action-based research (including design science and intervention-based research; $n = 16$; Fig. 6). More conceptual approaches ($n = 15$) and experiments ($n = 12$) precede the less frequently applied methods of analytical modeling ($n = 6$), literature reviews ($n = 5$), surveys ($n = 4$), and computational experiments ($n = 3$). Nevertheless, multiple assignments of research methods per article were possible and common. Especially, action-based research or engineering papers often validated the developed artifacts in the end with case studies, experiments, or surveys.

Only four authors published more than one article in this field, i.e., two each—while Kim et al. (2006) and Lee et al. (2011b) were co-authored by the same two authors, among others (Table 6).

The two papers with the most citations to date are Egger and Masood (2020) and Eppler and Platts (2009) with 176 and 160 citations, respectively. Furthermore, the five most cited papers account for almost 40% of the total citations of the 64 papers evaluated (Fig. 7).

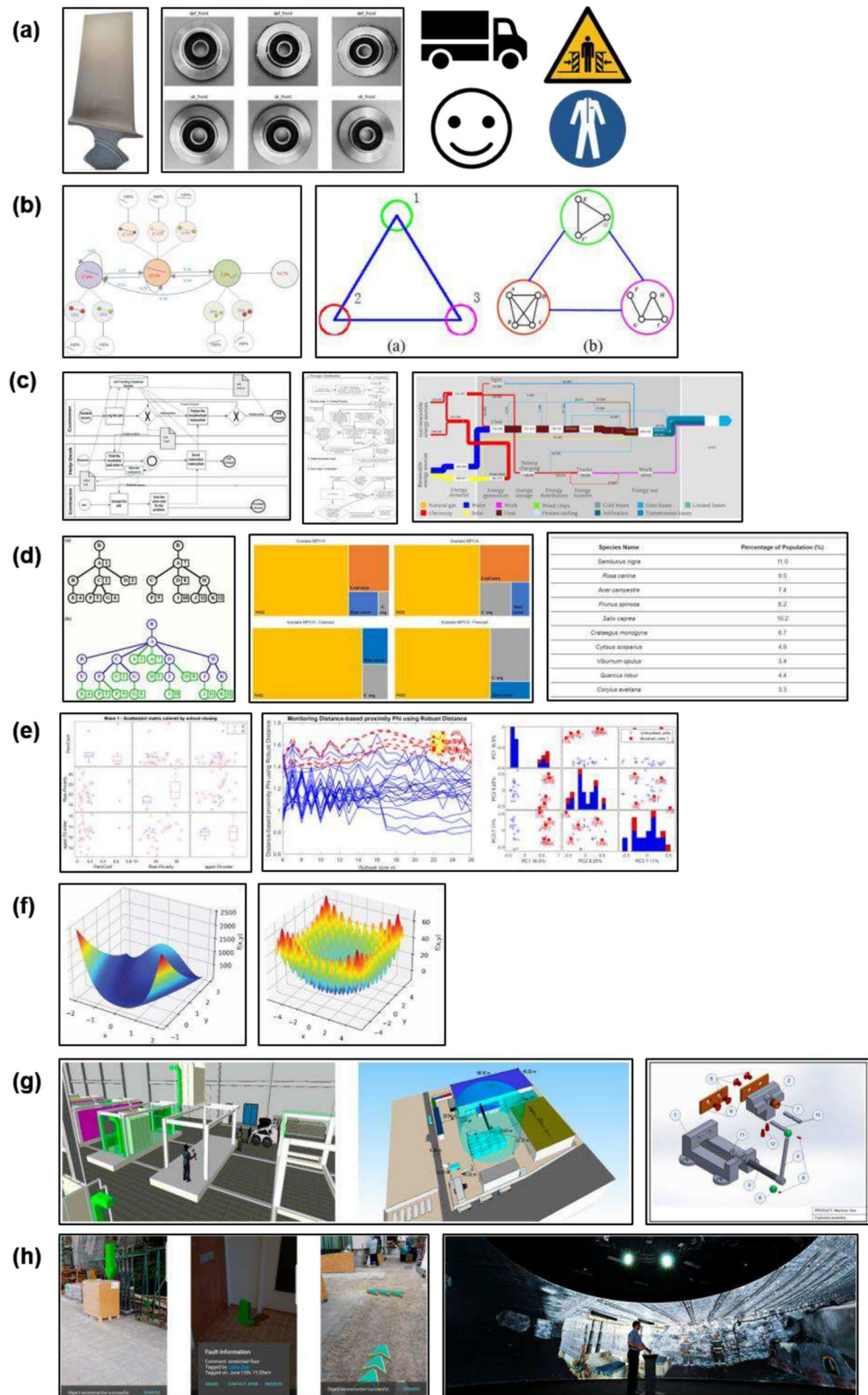
The bibliographic overview shows that there are no clear trends or patterns recognizable in terms of the number of publications per year (Fig. 4) or the number of scholars who are constantly contributing to the specific field (Table 6; Fig. 7). The choice of methods (Fig. 6) and journals (Fig. 5) is also quite diverse, ranging from management and social science approaches to engineering. In the following, the literature is further analyzed in detail according to its content and operational context clusters, as well as to our integrative framework on behavioral and visual mechanisms (Table 2).

4.2 Literature classification

In Appendix: Table 19 the overview of the assessed literature and assigned categories (Table 5) per reference is depicted. It allows to identify both the category assignments per paper as well as the overall number of assignments per category.

Table 7 offers an additional point of view on the assessed literature by positioning it along both the eight operational as well as visualization clusters. This depiction allows to quickly identify the major types of visualizations that are investigated in specific contexts or not. In the following sections, the literature will then be presented more in detail along the eight operational context categories concerning

Fig. 3 Examples for the different types of visualizations used as categories in the content analysis: **(a)** Images and Figurative (Aust et al. 2021; Sundaram and Zeid 2023). **(b)** Graphs and Networks (Liang et al. 2018; Pu et al. 2017). **(c)** Flow Charts (Venkatraman and Venkatraman 2019; Ho et al. 2021; Freis et al. 2016). **(d)** Hierarchies and Tables (Hebrard and Taylor 2016; Zanzi et al. 2021). **(e)** 2-Dimensional (Grané et al. 2021). **(f)** 3-Dimensional (Janssen et al. 2023). **(g)** Computer-Aided X (Lee and Kim 2017; Salah et al. 2019). **(h)** Augmented and Virtual Reality (Carius et al. 2022; Pedram et al. 2021). Note that Fig. 3 is neither intended to comprehensively depict all respective types of visualization nor to serve as a good- or best-practice reference. It is solely meant to give an idea of types of visualizations for our categories that are used in the literature in general—not necessarily in the literature that was assessed for this review



their major themes and topics according to our conceptual framework for visual and behavioral mechanisms in operations (Table 2).

4.2.1 Product development and design (Table 8)

Visualizations during the product development and design phase have been found the most frequently in the overall

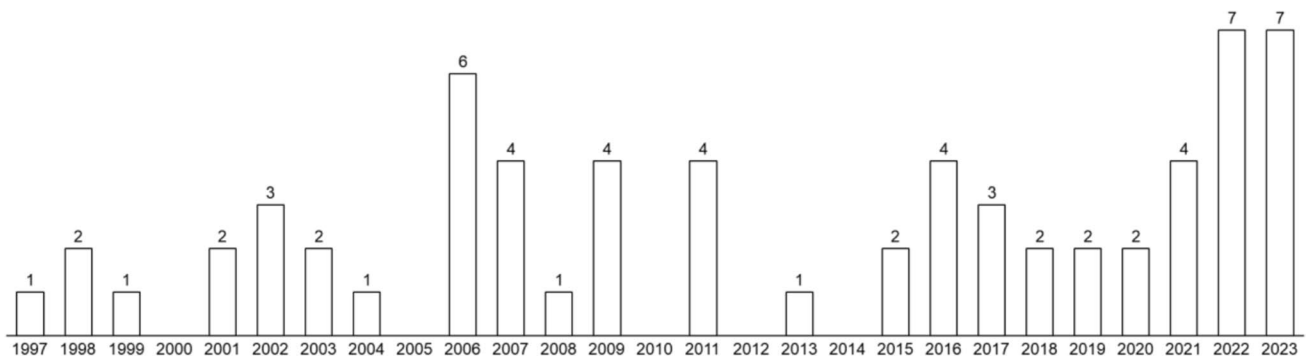


Fig. 4 Distribution of assessed articles per year of publication ($n = 64$)

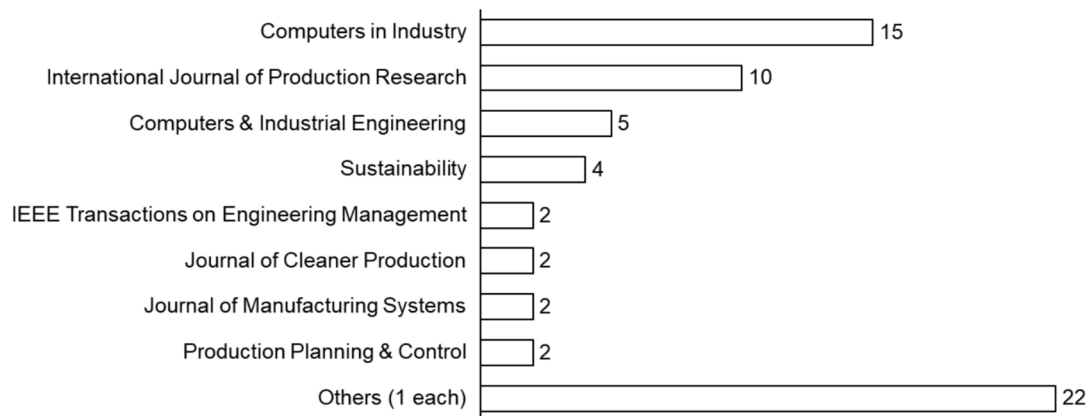
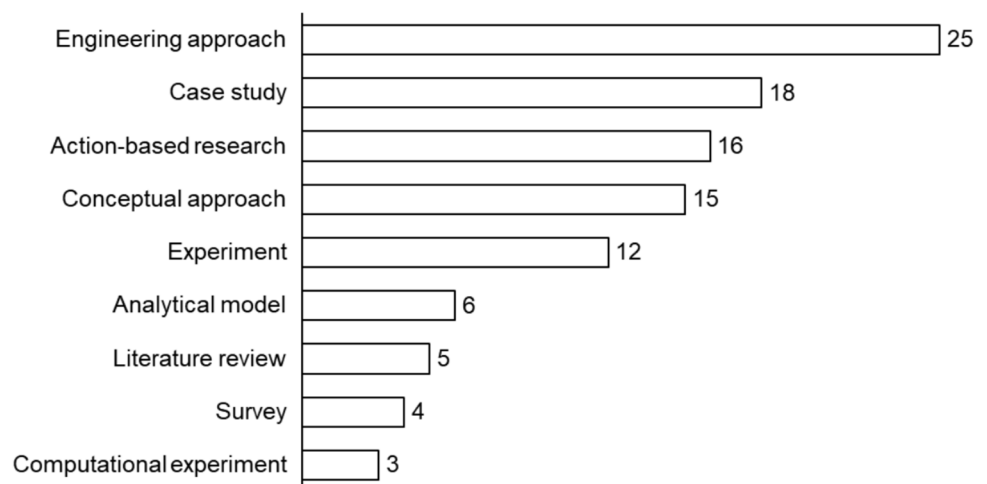


Fig. 5 Distribution of assessed articles per journal ($n = 64$)

Fig. 6 Distribution of applied research methods in the assessed articles (multiple assignments per article possible)



literature corpus ($n = 22$; Appendix: Table 19). The focus in this cluster lies on visualizations based on CAX data for realistic, digital representations of products and product parts, including their physical characteristics ($n = 12$; Table 7). Such representations are meant to improve the communication and collaboration among (distributed) engineering teams, but also

with external stakeholders like customers (Song et al. 2009; Yap et al. 2003; Zhang et al. 2004). By explicating engineers' mental images of product properties, implicit knowledge, and information can be visually shared with others, esp. using CAD data and software with additional product or design information like parametric/mathematical information (Yap

Table 6 Authors represented with more than one publication in the literature reviewed

Author	References
Han, S	Kim et al. (2006), Lee et al. (2011b)
Krivosnozhko, VE	Afanasiev et al. (2020), Førsund et al. (2009)
Stowasser, S	Stowasser (2006), Zülch and Stowasser (2002)
Yang, J	Kim et al. (2006), Lee et al. (2011b)

et al. 2003; Corallo et al. 2022; Vernica et al. 2023) or economic information like costs (Yoo and Kang 2021). The realistic virtual (and interactive) representation of an object is often complemented by exploded views of the objects, showing their various parts slightly separated from each other to visualize their relationships or order of assembly (Chung and Peng 2008; Kim et al. 2015; Yap et al. 2003). Additional benefits of using CAX in the development and design context are meant to be increased innovation capabilities and shorter development cycles (Yap et al. 2003), as well as lead times, improved quality, and employee efficiency (Hvam and Ladeby 2007). Technical improvements in terms of computational performance are also considered (Kim et al. 2015). Often, in the technical context of CAX the use of Virtual Reality Modeling

Language (VRML) file format or other technical solutions for web-based collaboration, data exchange of 3D objects, and visualization are part of the investigations (Choi and Samavedam 2002; Chung and Peng 2008; Kim et al. 2015; Song et al. 2009; Zhang et al. 2004). Choi and Samavedam (2002) make further use of the CAD data by simulating with it a rapid prototyping process, i.e., materializing the digital visualization of an object using additive manufacturing (3D printing).

While most of these studies follow engineering approaches and action-based research with eventual tests of the developed artifacts using case studies or computational experiments, the study of Yap et al. (2003) stands out by pursuing a more qualitative research approach. By conducting case study research at two companies using interviews, organizational artifacts, and observations as data sources, the authors manage to identify organizational benefits of the use of CAX in the context of knowledge explication like shorter development cycles, improved product designs, or reduced design, prototyping, and manufacturing costs. In doing so, Yap et al. (2003) conduct their research considering the concepts of mental models (Johnson-Laird 1980) and dual process theory (Leonard and Straus 1997).

Similar prominent in the product design context is also the use of VR technology (n = 4; Table 7), which is often

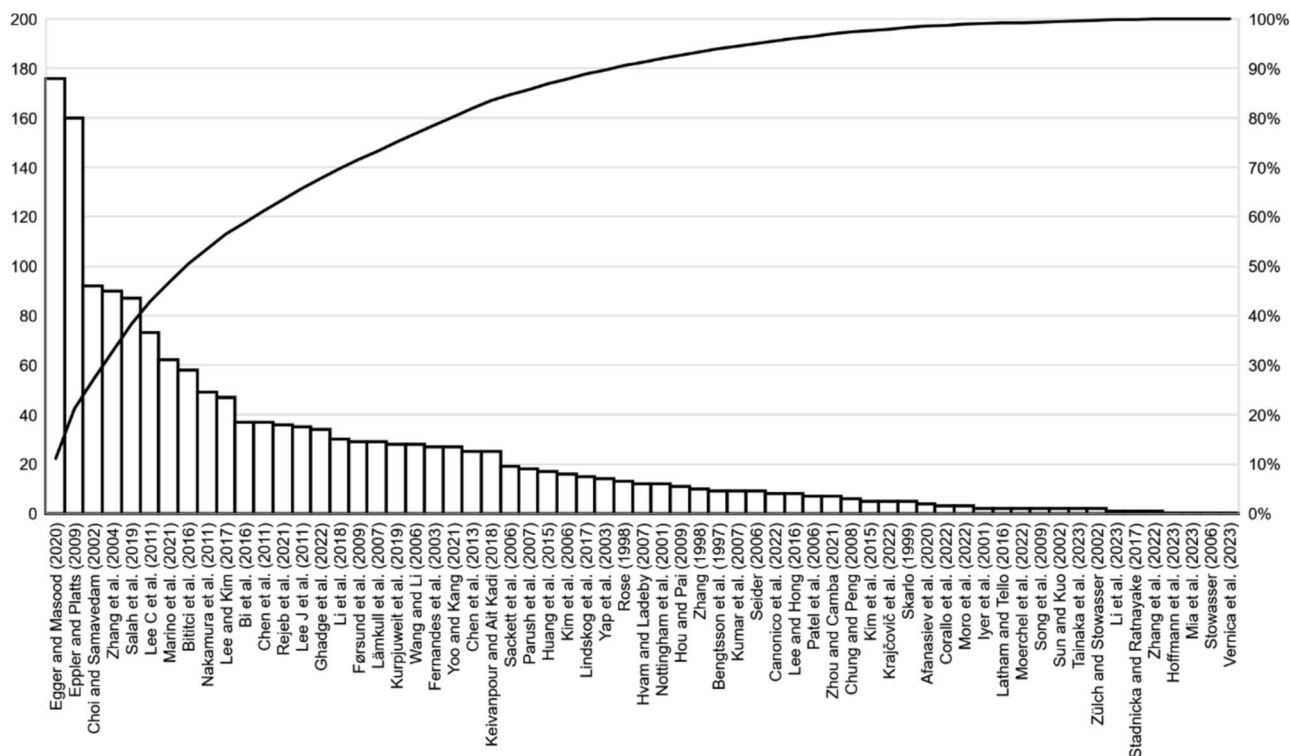
**Fig. 7** Number of citations per evaluated article (bars) and cumulative distribution of total citations (data accessed from Crossref on October 30, 2023)

Table 7 Classifying the literature according to manufacturing and operational context as well as type of visualization (using the ID for each reference from Appendix: Table 19)

Context	Visualization							
	Images/Figura- tive	Graphs/Net- works	Flow Charts	Hierarchies/ Tables	2D	3D	CAX	AR/VR
Product Development	25, 50, 58	14	5, 36, 58	17, 50	17, 50, 61	–	2, 8, 15, 18, 20, 25, 41, 46, 47, 51, 61, 62	7, 19, 25, 34, 51
Manufacturing Layout	25	–	–	–	–	–	2, 22, 25, 27, 28, 29, 30	19, 25, 54, 60, 63
Production Planning								
37	42, 49	24	36, 42	44	1, 12, 24, 47, 49	40, 47	2, 16, 27, 28	64
Production Control								
37	42, 43	–	36, 42	57	1, 3, 6, 31, 32, 56, 57	3, 57	43, 56	–
Shop Floor Management								
37	21, 43	–	21	–	–	–	30, 43	9, 30
Supply Chain Management								
37	–	–	53	33	52	–	–	35
Education/ Training	–	–	–	–	13	–	13, 38, 45	11, 38, 55
Organizational/ Strategical	4, 10, 23, 49	10, 24	4, 10, 24, 59	4, 10, 23, 24, 39	4, 10, 23, 24, 26, 49	–	–	–

closely related to CAX, as it uses the CAX data to visualize the digital objects in virtual (immersive) environments via head-mounted displays (HMDs) or CAVEs (computer-aided virtual environments). While engineering approaches and experiments are also used here, the design and evaluation of the visualizations are way more user-centric, i.e., behavioral aspects are more at the center of these studies. E.g., Patel et al. (2006) consider perception for the correct depiction and recognition of virtual materials by experts.

Another focal theme in this cluster is the use of visualizations for improved knowledge representations in the design process, where different kinds of representations are investigated like (undirected) network graphs to depict relations between lessons-learned documents (Huang et al. 2015), flow charts to capture manufacturing process knowledge in the design phase (Chen et al. 2011), hierarchies using treemaps or hexagonal binning to integrate environmental considerations (Keivanpour and Ait Kadi 2018), or additionally icons and symbols (Canónico et al. 2022).

Additionally, Kumar et al. (2007) present a visualization of the relation between assembly tolerances of a product and development and expected total manufacturing costs by relating both in a two-dimensional Cartesian coordinate system. And Lee et al. (2011a) use different means of visualization

like networks and flow charts to represent changes in patents to improve an organization's capability to react to technological trends, while Moerchel et al. 2022 develop a notation language to simplify the mapping of intellectual property risks.

4.2.2 Manufacturing layout, including workplace design and ergonomics (Table 9)

Visualizations to help lay out facilities or manufacturing systems ($n = 11$; Appendix: Table 19) are similarly characterized as in the previous cluster and cannot be strictly separated from each other, as the manufacturing layout and design of workplaces are often contingent on the product designs and vice versa. Nevertheless, in contrast to the product design cluster, the types of visualizations investigated here, are almost solely CAX ($n = 7$; Table 7) and AR/VR ($n = 5$; Table 7). Additionally, a higher fraction of articles in this cluster considers behavioral aspects, as well. This is since workplace design and ergonomics, including worker support and assistance (Hoffmann et al. 2023; Tainaka et al. 2023; Zhang et al. 2022), make up a large part of the cluster (Bengtsson et al. 1997; Lämkuill et al. 2007; Li et al. 2018), where human factors are essential per se.

In these cases, especially the correct ergonomic ratings of workplaces and processes using different visualizations are of interest to ensure the best possible safety for the workers during their task execution. Bengtsson et al. (1997) compare the usefulness of paper and computer drawings of manufacturing and workplace layouts for the evaluation of different planning issues. Similarly, Lämkuil et al. (2007) compare four different computer models of human appearances for correctly assessing the depicted human workload. They find that the appearance of the presented manikin influences especially non-ergonomists in their evaluation. And Li et al. (2018) present a 3D visualization-based ergonomic risk assessment method and find it superior to manual observations of work postures in terms of accuracy.

The literature concerning ergonomic aspects can thereby often rely on standardized methods to determine the quality of the decisions resulting from the use of different visualizations. So, e.g., the Working Posture Analyzing System (OWAS), Rapid Entire Body Assessment (REBA), or Rapid Upper Limb Assessment (RULA) are applied (Li et al. 2018). Concerning worker assistance systems using AR, the effectiveness of the visualized affordances to the worker are of interest like recall and precision, but also cognitive, i.e., workload, and physical strain (Hoffmann et al. 2023; Tainaka et al. 2023; Zhang et al. 2022).

Other studies in this cluster focus on the layout or redesign of factories and production systems (Kim et al. 2006; Lee et al. 2011b; Lindskog et al. 2017). While Kim et al. (2006) and Lee et al. (2011b) investigate the design and use of VR environments for manufacturing layouts, Lindskog et al. (2017) test the creation of realistic 3D CAD visualizations of machinery using 3D laser scanning.

The most prominent methods followed are engineering approaches, resp. action-based research, and experiments, that are often complemented by case studies or surveys.

4.2.3 Production planning, including data envelopment analysis (Table 10)

Visualizations in the context of production planning are the subject of the second most articles overall ($n = 14$; Appendix: Table 19). Again, visualizations of computer-aided process planning (CAPP) and other CAX are represented the most along with 2D data visualizations ($n = 4$ and $n = 5$; Table 7). Iyer et al. (2001), e.g., develop a STEP (standard for the exchange of product model data) parser in a testbed environment to support machining process simulation and CAPP. Lee and Kim (2017) used the CAD product data with production process information to develop a 4D BIM (building information modeling) simulation to improve operations in the manufacturing of construction modules and Zhou and Camba (2021) develop an immersive process planning approach using VR.

A prominent operational sub-context concerns 2D visualization in data envelopment analysis (DEA) or for production possibility sets (Afanasiev et al. 2020; Førstund et al. 2009), whereas there are no specific human factors considered. Within both these approaches analytical modeling and computational experiments are used as methods. Førstund et al. (2009) use visualization to represent production frontiers for multi-input multi-output models. And Afanasiev et al. (2020) optimize the solution time for visualizing production possibility sets using algorithms for parallel computation.

Further visualizations in this cluster include images and figurative representations, process and flow charts, as well as data visualizations situated in 3D coordinate systems ($n = 2$ each). Both Rose (1998) as well as Stadnicka and Ratnayake (2017) investigate the optimal use of flow representations for engineering/production information and resources. Stadnicka and Ratnayake (2017) consider for this purpose the concepts of value stream mapping (VSM) and value stream design (VSD) that also rely on icons and symbols to depict manufacturing flows. Skarlo (1999) uses 3D surface visualizations of different variables like production volume and mix to show impacts on profits. Zhang (1998), however, developed and tested both 2D and 3D visualizations of different production pull lines (assembly lines) and respective product and demand satisfaction over time to help production planners generate alternative plans. Thereby, Zhang (1998) explicitly considered perceptual and problem-solving processes of humans and visualization construction guidelines, as well as evaluation methods like cognitive walkthroughs.

Sun and Kuo (2002) design a small multiples design with table graphs to enable the visual exploration of multidimensional production data stored in relational databases.

Noteworthy in the context of production planning is also the literature review of Sackett et al. (2006) due to its focus on cognitive mechanisms when using visualizations in manufacturing sequence management like focus attention, triggering memory, stimulating thinking, or bridging missing information. Sackett et al. (2006) therefore ground their review both on visualization principles and functionalities as well as cognitive fit theory (Vessey 1991) to determine visualizations' suitability for manufacturing sequence management tasks.

Overall, in this operational context, still, engineering and action-based research are widely adopted, but also analytical modeling, computational experiments, and conceptual approaches are used to investigate visualizations for production planning.

4.2.4 Production monitoring and control (Table 11)

The context of production monitoring and control ($n = 11$; Appendix: Table 19) has as well considerable overlaps with the previous context of production planning. Here, mostly

2D-based data visualizations are applied to monitor and control multi-dimensional (input-output) production data and process parameters ($n = 5$; Table 7). Nottingham et al. (2001) present star (glyph) plots to visualize process parameters, while Nakamura et al. (2011) design a 2D matrix visualization of the unit physical input-output by materials as an alternative to a Sankey diagram for material/substances flow analysis. And Chen et al. (2013) show how visual assessment of data quality improves prognostic and health modeling of manufacturing systems. Mia et al. (2023) develop visualization methods to display machining data for control purposes using and combining various visual means like sunburst diagrams and CAD data with process and product parameters.

But Bi et al. (2016) also use 3D bar chart visualizations on a location map for monitoring wireless sensor networks in production environments to monitor them in real time, and Li et al. (2023) develop a digital twin to monitor and visualize the status of industrial robots.

The visualizations in this cluster are primarily designed to highlight and synthesize important data that requires attention for monitoring or corrective action because the human cannot keep track of the raw data. This is achieved by visualizing central tendencies, such as averages, of production and process data associated with machines and materials. The result of production system performance is improved process and product quality.

Action-based research, including case studies for evaluation purposes, is the most frequently applied method in this cluster.

4.2.5 Shop floor management (Table 12)

On the shop floor level ($n = 5$; Appendix: Table 19), visualizations to manage and guide especially the workers based on images, icons, and symbols, as well as CAX and AR/VR are investigated ($n = 2$ each; Table 7). Visual management as a sub-context within shop floor management, based on lean principles for effective guidance and communication on the shop floor, is evaluated by Kurpjuweit et al. (2019) concerning its success factors and barriers during organizational implementation applying case study research.

Differently from the clusters of product design and manufacturing layout, here AR is more prominently represented than VR, e.g., in the literature review of Egger and Masood (2020) or the study of Marino et al. (2021). According to these, AR is assessed in maintenance, assembly, quality, or logistics. For evaluation of the use of the AR technology, often the NASA Task Load Index (TLX) to measure the cognitive strain of the users, and/or the System Usability Score (SUS) is applied.

Whereas the overall research methods in this cluster are quite diverse from analytical modeling over case study

research and experiments to action-based research or literature review, Stowasser (2006) uses various data and methods from eye tracking, log files, video recordings analysis, as well as structured interviews to determine the optimal visual support on the shop floor, while considering task-specific and psychological aspects like strain.

4.2.6 Supply chain management (Table 13)

In SCM contexts in specific ($n = 5$; Appendix: Table 19), different tabular and hierarchical data representations in an enterprise resource planning (ERP) system are evaluated via experiments (Parush et al. 2007), as well as AR in logistics and SCM is reviewed (Rejeb et al. 2021). Ghadge et al. (2022) use system dynamics to visualize the interdependencies, such as nonlinear relationships, and causalities between influencing factors of the COVID-19 pandemic on ripple effects in supply chains. The goal is to make the relationships more transparent to decision makers in the face of SC disruptions. Ferreira et al. (2023) apply an action research approach to develop and test a comprehensive system of data models and visualizations to improve fleet management by presenting performance indicators such as maintenance or fleet distribution over time in a dashboard.

Behavioral mechanisms include improved problem solving and decision making due to reduced cognitive load and easier recall (Parush et al. 2007; Ferreira et al. 2023), engagement in warehouse tasks using AR (Rejeb et al. 2021), and transparency and elicitation of SC disruption effects (Ghadge et al. 2022).

4.2.7 Education and training (Table 14)

In the cluster of education and training ($n = 5$; Appendix: Table 19), 3D data visualizations of text-based knowledge extraction (Hou and Pai 2009) as well as realistic visualizations of training environments via 3D (Wang and Li 2006) or VR (Fernandes et al. 2003; Salah et al. 2019; Krajčovič et al. 2022) are investigated using action-based research, engineering approaches, and experiments. Fernandes et al. (2003) even design a walkable VR sphere to support training for certification requirements of a new assembly planning process by enabling full immersion.

In the education cluster, the behavioral focus is on sharing and explication of knowledge as well as learning performance and motivation. Using the possibilities of immersion via AR and VR, models of reality are visualized and enriched with (implicit) knowledge and interaction possibilities. These visualizations aim to facilitate recall, mutual understanding of basic (abstract) concepts, and collaboration among users to solve problems. The goal is to improve worker performance and learning, as well as motivation through engagement.

4.2.8 Entrepreneurship, organization, project management, and service-orientation (Other; Table 15)

Concerning entrepreneurial, organizational, project-, and service-oriented contexts of manufacturing companies ($n = 8$; Appendix: Table 19), besides 2D visualizations ($n = 6$; Table 7) as well as hierarchies and tables ($n = 5$; Table 7), visualizations with focus on realistic images or icons and signs with relations to real objects or abstract ideas were mainly considered. Here, most of the papers per cluster are specifically addressing behavioral aspects using visualizations, especially for strategic planning and decision-making (Bititci et al. 2016; Eppler and Platts 2009; Latham and Tello 2016). Here the most emotional aspects of visualizations are addressed, as many of the visualizations in this cluster are specially meant to engage, motivate, or persuade internal and external stakeholders, e.g., to improve strategic (group) decision-making (Bititci et al. 2016; Eppler and Platts 2009; Latham and Tello 2016), collaboration (Zülch and Stowasser 2002) or value-driven business models (Moro et al. 2022).

Notably, this is almost the only cluster where visualizations are meant to support managers in decisions with uncertain or non-deterministic outcomes—besides some other articles on visualizations in the production planning cluster.

Other authors here are concerned with visualizing capacity constraints in companies' project portfolios (Seider 2006) or visualizing industrial service clusters on the market using companies' annual reports and hexagonal bin plots (Lee and Hong 2016).

The most common research method applied in this cluster is case study research, followed by conceptual approaches.

5 Synthesis and propositions

After presenting the results of the literature review, analysis, and classification in the preceding sections, we will synthesize the findings in general and in particular regarding the behavioral mechanisms of visualizations for manufacturing operations, and suggest further research and development directions in this regard, thus answering RQ 2 (Section 1).

5.1 Framework and classification of visualizations for manufacturing operations

First, we present the identified visualizations in manufacturing operations according to the four main parts related to our applied review method using CIMO logic (Denyer and Tranfield 2009; Section 3.1). Each part is further underpinned by the categories and codes of the content analysis (Sections 3.2, 4) and other noteworthy aspects as reported in the findings section. The four main parts of the framework, which are also interrelated, are operational contexts, visual

means, social, cognitive and emotional aspects, and behavioral and performance outcomes (Fig. 8).

One contextual aspect that became apparent, and that is also propagated by the Y-CIM-model of Scheer (1995) for computer-integrated manufacturing (CIM), is the use and necessity of information systems—or in our case visualizations—for both management (business administration) and manufacturing (technical/engineering) processes in production companies. Although these processes from both realms, like master production planning (management) on the one hand, and product design (engineering) on the other, need to run in parallel and be interlinked, they require or make use of different systems and architectures. According to our findings, similar things are also true concerning the use of visualizations in manufacturing and operations management. While on the technical side, CAX systems and visualizations e.g., in production design and manufacturing layout were most prominent, visualizations concerning managerial processes and contexts were more diverse. Therefore, we added a non-discrete distinction between more business- and more technical-related uses of visualization contexts in our framework (Fig. 8).

The types of visualizations in the framework (Fig. 8) are enhanced by notable findings from our analysis (Section 4) like further specifications of treemaps or table graphs as visualizations of hierarchies and tables. Concerning the investigated mechanisms that are relevant for the use of visualizations in operational contexts, we added besides the behavioral aspects (social, cognitive, and emotional) also technical ones that are solely referring to applied or achieved computational improvements, e.g. However, the technical aspects may both refer to mechanisms and outcomes of the interventions (visualizations) as they can often be considered both. At the same time, e.g., increased display resolutions can also be relevant for greater immersion as an emotional mechanism concerning VR applications.

The further behavioral mechanisms that apply when using visualizations concern e.g., knowledge explication and sharing within groups or with external stakeholders, several cognitive processes, theories, and measurements like mental models, cognitive load, dual process theory, pre-attentive processing, or the NASA TLX. Additionally, some emotional aspects regarding beliefs, attitudes, or the identification with human models may play a role when using visualizations in manufacturing contexts.

In addition to the behavioral and technical outcomes, the framework also presents influences of the use of visualizations on organizational performance like reduced development cycle times using CAX representations and tools, higher accuracy (quality) when using AR for maintenance, or reduced manufacturing costs through optimized decision-making processes.

Finally, based on the evaluation of the literature per operations cluster (Sections 4.2.1–4.2.8) and the summary of the

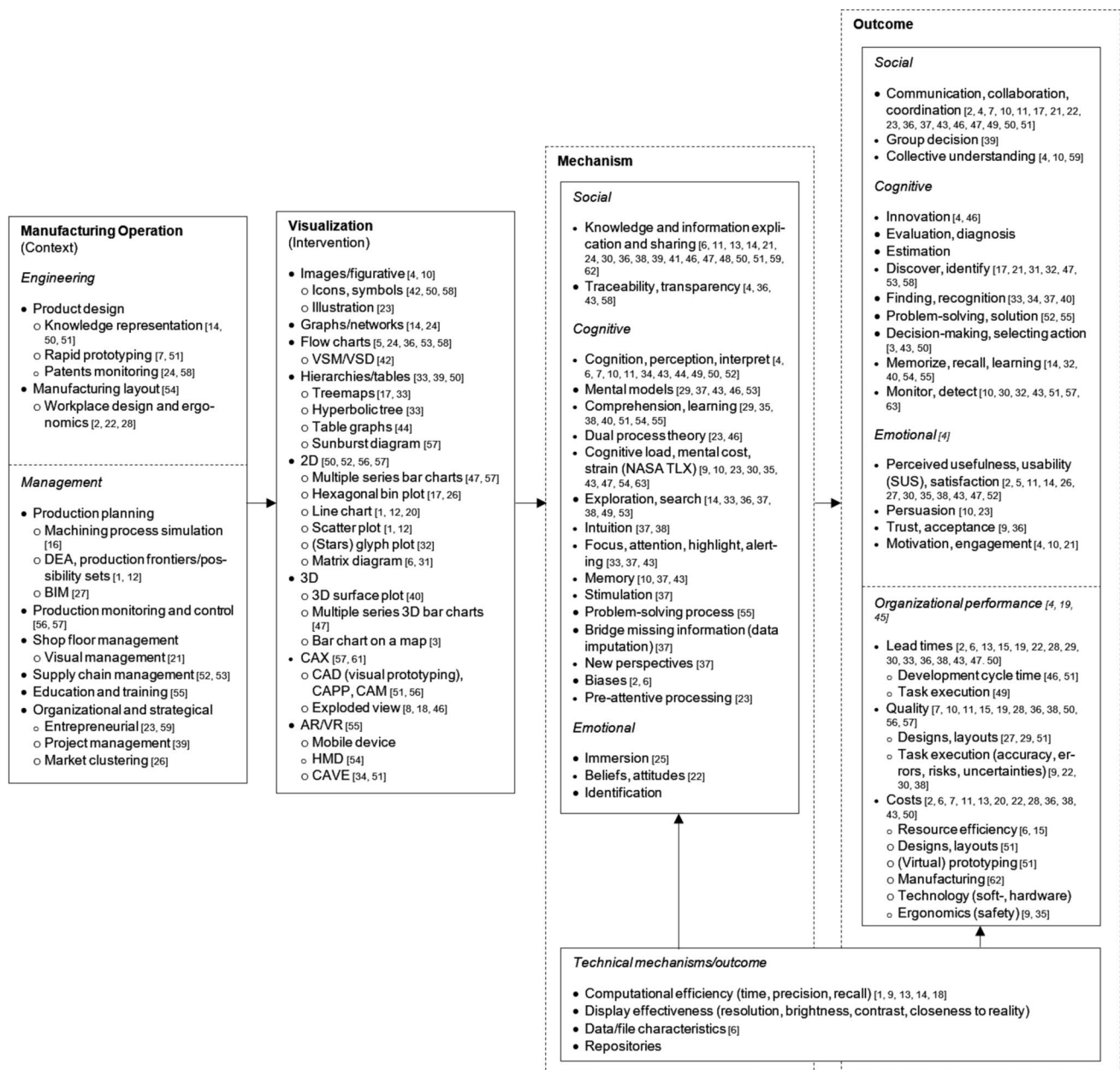


Fig. 8 Derived framework from the literature relating manufacturing operations, visualizations, behavioral aspects, and outcomes to each other [depicting indicative references using the respective IDs from Appendix: Table 19]

main characteristics of respective visualizations (Tables 8, 9, 10, 11, 12, 13, 14, and 15), we further classify their application per cluster (Table 16).

To summarize our observations from the literature, we find that visualizations in product development are almost purely engineering-related. Therefore, they try to achieve exact representations of real (simulated) object properties. Consequently, increasingly powerful and complex interactive visualization methods, mainly based on CAX technology, are being developed to achieve more efficient and detailed representations. These tools aim to improve

collaboration between designers, engineers, and customers by facilitating the creation and sharing of mental models. That is, social mechanisms between visuals and operations are in focus to prescribe future designs.

Both engineering and management visualizations are used for manufacturing layouts and production planning. They often combine CAX data with ergonomic and economic information to help prescribe production systems and processes. The visualizations address cognitive mechanisms due to bounded rationality and mental workload to identify patterns and alternatives for improvement.

Table 8 Summary of the product development and design cluster according to the conceptual framework

Framework			Product development and design
Context (C)	When?		Patent monitoring; new product development
	Content (what?)		Relations of intellectual properties; physical characteristics (of materials, parts, products), machining and production process data
Intervention (I)	Benefit (why?)	Semiotic framework	Demonstrating properties, associations, and causal relationships with replications of reality and by connecting properties over time: simulating reality, testing alternative designs and properties
	Method (how?)		Comprehensive system depiction: Graphs and networks; CAX, VR, hierarchies and tables, flow charts
Mechanism (M)	Behavioral		Knowledge sharing, communication, collaboration, understanding, cognitive reflection, boundedly rational, cognitive overload, availability bias, creativity
	Visual		Elicitation, exhaustive comparisons, shared mental images and models, integrating different perspectives, showing interdependencies, easier sequencing, recency effect, inspire
Outcome (O)			Increased innovation capabilities, shorter development cycles, improved product/process quality and employee efficiency, engagement

Table 9 Summary of the manufacturing layout cluster according to the conceptual framework

Framework			Manufacturing layout
Context (C)	When?		Lay out facilities and manufacturing systems, workplace design, ergonomics; worker assistance
	Content (what?)		(Approximations of) physical properties, models, processes, spatial distances, movements, strain, affordances
Intervention (I)	Benefit (why?)	Semiotic framework	Demonstrating properties, associations, and causal relationships with replications of reality: simulating/snapshots of reality, testing alternative designs and properties; signaling, informing
	Method (how?)		Single attributes, multiple dimensions: CAX, AR/VR; icons and symbols
Mechanism (M)	Behavioral		Boundedly rational, cognitive reflection, cognitive overload
	Visual		Elicitation, easier sequencing, showing interdependencies, more exhaustive comparisons, salience
Outcome (O)			Improved layout quality, ergonomics, workplace safety, costs, cycle times

Table 10 Summary of the production planning cluster according to the conceptual framework

Framework			Production planning
Context (C)	When?		Manufacturing sequence planning, data envelopment analysis, production possibility sets, material and information flows, master production planning
	Content (what?)		Production and demand data, costs and profits, cycle times, processes
Intervention (I)	Benefit (why?)	Semiotic framework	Demonstrating properties, associations, and causal relationships between production factors and economic variables
	Method (how?)		Using summaries of central tendencies, expected values, multidimensional subsets: flow charts, scatter plots, line graphs, binning, frequencies, densities, value stream mapping and design (icons), hierarchies and tables
Mechanism (M)	Behavioral		Boundedly rational, cognitive reflection, judgement bias, reference dependency, cognitive dissonance, availability bias
	Visual		Facilitate elicitation and synthesis, exhaustive comparisons, easier sequencing
Outcome (O)			Improved production system performance like utilization, lead times, costs, profits, service levels

Table 11 Summary of the production monitoring and control cluster according to the conceptual framework

Framework			Production monitoring and control
Context (C)	When?		Process monitoring, production control, quality management
	Content (what?)		Production, process, and sensor data
Intervention (I)	Benefit (why?)	Semiotic framework	Demonstrating properties and associations
	Method (how?)		Summaries of central tendencies, expected values, and multidimensional subsets of multiple rich observations: line graphs, glyphs, matrices, hierarchies and tables, bar charts, flow charts
Mechanism (M)	Behavioral		Bounded rationality, cognitive reflection, judgement bias, reference dependency, availability bias
	Visual		Elicitation, salience, easier recall and sequencing, recency effect
Outcome (O)			Improved process and product quality and production system performance such as cycle times and utilization

Table 12 Summary of the shop floor management cluster according to the conceptual framework

Framework			Shop floor management
Context (C)	When?		Worker management, visual management, worker assistance
	Content (what?)		Production and process data and deviations, signals, affordances
Intervention (I)	Benefit (why?)	Semiotic framework	Demonstrating properties without associations
	Method (how?)		Summaries of central tendencies, expected values and analogies: icons and symbols, bar charts, flow charts, AR
Mechanism (M)	Behavioral		Bounded rationality, cognitive reflection, availability bias, collaboration and coordination, culture
	Visual		Elicitation, salience, easier recall and sequencing, tracking, showing interdependencies, engagement
Outcome (O)			Improved worker efficiency and production system performance

Table 13 Summary of the supply chain management cluster according to the conceptual framework

Framework			Supply chain management
Context (C)	When?		Sourcing, logistics, commissioning, fleet management, risk / disaster management
	Content (what?)		Buyer-supplier, supply chain, network, logistics, and spatial data
Intervention (I)	Benefit (why?)	Semiotic framework	Demonstrating properties, associations, and causal explanations
	Method (how?)		Multidimensional subsets and comprehensive system depictions demonstrating dynamics: hierarchies and tables, flow charts, bar charts, line charts, scatter plots, icons, AR
Mechanism (M)	Behavioral		Bounded rationality, cognitive reflection, judgement bias, reference dependency, cognitive dissonance, availability bias
	Visual		Elicitation, easier recall and sequencing, exhaustive comparisons, tracking and showing interdependencies
Outcome (O)			Improved supply chain and logistics performance such as service levels, capacities, inventories, outage risks

Table 14 Summary of the education and training cluster according to the conceptual framework

Framework			Education and training
Context (C)	When?		Engineering / management education, training-on-the-job, virtual training
	Content (what?)		Knowledge, concepts, ideas, affordances
Intervention (I)	Benefit (why?)	Semiotic framework	Demonstrating properties, associations, and causal explanations based on analogies and replications of reality
	Method (how?)		Comprehensive system depiction: AR/VR
Mechanism (M)	Behavioral		Bounded rationality, cognitive reflection, availability bias, communication, collaboration
	Visual		Elicitation, easier recall, mutual understanding, showing interdependencies
Outcome (O)			Improved worker performance, learning outcomes, motivation

Table 15 Summary of the other operations cluster according to the conceptual framework

Framework			Other
Context (C)	When?		Entrepreneurship, organization and project management, service-orientation
	Content (what?)		Ideas, concepts, plans, actions, implementations, opinions, image
Intervention (I)	Benefit (why?)	Semiotic framework	Demonstrating properties and associations
	Method (how?)		Analogies and emblematic multidimensional snapshots and dynamics: icons, images, bar charts, line charts, pie charts, flow charts, hierarchies and tables, graphs, networks
Mechanism (M)	Behavioral		Bounded rationality, cognitive reflection, availability bias, cognitive dissonance, communication, collaboration, culture, power, social embeddedness
	Visual		Elicitation, synthesis, exhaustive comparisons, channel thinking, recall and sequencing, mutual understanding, tracking and showing interdependencies, integrating different perspectives, engage, inspire, and persuade
Outcome (O)			Raising stakeholder interest, meeting customer demands, strategic group decision making, shared visions, culture, and plans

However, in plant layout or workplace design, model-like representations of reality are more prevalent than in production planning, where more abstract data representations and flowcharts are used to determine optimal manufacturing sequences and the like.

Except for education and training, the other five operational clusters almost exclusively use visualizations for management data. In production management and control as well as in shop floor management, descriptive and predictive purposes of visualizations are important, especially to draw the attention of the decision maker to specific deviations from expectations (cognitive mechanisms), but also to convey affordances to shop floor workers and to coordinate them (social mechanisms) to improve worker management. Visualizations with clear highlighting of important aspects, as well as icons or symbols that enhance preattentive processing, are beneficial here to achieve improved operational performance.

While supply chain management combines many of the characteristics of the previous clusters, it is particularly

concerned with the coordination and transparency of complex buyer-supplier relationships, networks, and logistics. To support this, visualizations that enhance information and knowledge sharing and highlight relationships and interdependencies are relevant. In addition to visualizations of central tendencies or frequencies, graphs, networks, and flowcharts are useful for planning and monitoring.

The education and training cluster is now almost entirely focused on the immersive capabilities of AR and especially VR. The near-realistic visualization of manufacturing environments is used to facilitate knowledge explanation and sharing processes (cognitive), foster collaborative problem solving (social), and motivate users (emotional mechanisms).

Besides the previous cluster of education, the organizational cluster is the only one that has a strong focus on the emotional mechanisms of visualization. Icons, symbols, and abstract representations are used to communicate complex concepts,

Table 16 Classification of visualizations in manufacturing and operations management according to the conceptual framework

Framework	Operations							
	Product design	Manufacturing layout	Production planning	Production monitoring and control	Shop floor management	Supply chain management	Education and training	Organizational and strategic
Classification	... Refer to Tables 8, 9, 10, 11, 12, 13, 14, and 15 ...							
	Engineering <i>Focus:</i> Engineering	Engineering /management <i>Focus:</i> Engineering /management	Engineering /management <i>Focus:</i> Engineering /management	Management <i>Focus:</i> Management	Management <i>Focus:</i> Management	Management <i>Focus:</i> Management	Engineering /management <i>Focus:</i> Engineering /management	Management <i>Focus:</i> Management
	<i>Purpose:</i> prescriptive <i>Mechanism:</i> social	<i>Purpose:</i> prescriptive <i>Mechanism:</i> cognitive	<i>Purpose:</i> prescriptive <i>Mechanism:</i> cognitive	<i>Purpose:</i> descriptive <i>Mechanism:</i> cognitive	<i>Purpose:</i> descriptive <i>Mechanism:</i> cognitive / social	<i>Purpose:</i> prescriptive / predictive <i>Mechanism:</i> cognitive / social	<i>Purpose:</i> prescriptive / descriptive <i>Mechanism:</i> cognitive / social / emotional	<i>Purpose:</i> prescriptive <i>Mechanism:</i> social / emotional
	Engineering-related visualizations that replicate reality to enhance shared mental models, communication and collaboration.	Engineering / management visualizations that model approximations of real production systems to elicit physical relationships and interdependencies.	Management-focused visualizations that depict properties and relationships at strategic and tactical levels, reducing mental workload and bounded rationality.	Management visualizations to highlight process deviations at tactical and operational levels and focus attention.	Management-oriented visualizations of production information at the operational level to signal required actions and convey affordances.	Management-oriented visualizations of supply networks, their performance and status at all operational levels improve planning, monitoring and transparency.	Engineering / management visualizations of manufacturing operations to share knowledge, foster understanding and motivate.	Management visualizations of complex, abstract concepts and ideas to develop mutual understanding and engagement.

ideas, and visions. They help to develop mutual understanding (social) and engagement of stakeholders for motivation and persuasion of organizational goals (emotional mechanisms).

5.2 Propositions for future research and development

Based on our literature review and analysis of visualization in manufacturing and OM, we derive propositions for further research and development efforts in this interdisciplinary field. We present our suggestions in two parts. These are, first, propositions according to gaps in the analyzed literature itself and in relation to previous literature and knowledge base in both fields, and second, concrete possibilities for interventions and testing hypotheses of visual means in BOM. In addition, for each proposition, we provide references in the existing literature as further clues and starting points for further endeavors in this regard by peers.

5.2.1 Propositions based on identified gaps in the analyzed literature and related to the general knowledge base

Proposition 1: Theoretical background *Except for honorable exceptions like Sackett et al. (2006) or Eppler and Platts (2009), few studies explain the theoretical foundations of operations behavioral psychology, let alone InfoVis. As this work has tried to show, we believe that it would be worthwhile to ground investigations of visualizations in manufacturing and operations management in the body of knowledge of both BOM and InfoVis, to allow the systematic design and evaluation of any further research and development study in this area. Regarding behavioral regularities in operations, you can refer to Bendoly et al. (2010), Donohue et al. (2018) and Fahimnia et al. (2019). Arnott (2006) and Arnott and Gao (2019, 2021) relate concepts from behavioral economics to the design and use of decision support systems, while Malinova and Mendling (2021) provide cognitive theories for the design of system representations. In addition, Eppler and Platts (2009), Bresciani and Eppler (2015), Bendoly (2016), and Basole et al. (2021) provide theoretical foundations and guidelines explicitly for visualizations in management contexts.*

Proposition 2: Over-reliable representations *Regarding visualization technologies in general, but CAX and AR/VR in particular, the underlying systems are becoming increasingly powerful and capable of presenting true representations of our physical world in digital (immersive) environments. As these systems are used especially in product design and education/training (Table 7), where imagination, creativity and cognitive activation are important, critical reflection and investigation of the influence of over-reliable representations on operational outcomes*

may be relevant (Table 1). To date, technological advances in this area have been viewed as improvements per se, including the introduction of digital twins (Li et al. 2023). However, overly reliable, i.e., highly elaborated visualizations may provoke less critical discussion than preliminary sketches (Bresciani and Eppler 2015). Especially in education and training, the concept of didactic reduction can facilitate learning. Too rigorously presented perspectives in visualizations may also exclude certain groups and opinions (Bresciani and Eppler 2015).

Proposition 3: Oversimplification and ambiguity *We see many of the cognitive biases in behavioral economics that arise from decision making under uncertainty (Tversky and Kahneman 1974), such as availability bias and reference dependence (Table 1). At the same time, we find many visualizations of engineering and management data in the literature reviewed that rely on summaries of central tendencies or expected values using single attributes (Tables 8, 9, 10, 11, 12, 13, 14, and 15). Such visualizations in uncertain economic environments may underestimate the true variability, distribution, or risk of important parameters for decision making. We therefore suggest that efforts be increased to systematically investigate and design visualizations that effectively integrate measures of ambiguity that can be easily perceived and processed by the decision maker.*

Proposition 4: Immersion *We see that immersive technologies such as AR/VR have not yet been explored or applied to production planning, control, or organizational operations in the literature reviewed (Table 7). However, because AR and VR are particularly powerful in creating immersion and thus engagement and motivation, it may be particularly relevant to explore them considering platforms such as Metaverse for communicating, collaborating, coordinating, and conveying complex, abstract ideas and visions.*

Proposition 5: Visualizations and emotions *Overall, emotional links between visualizations and operations have been investigated the least (Table 16). Nevertheless, we consider the emotional benefits of visualizations as a promising line of research to follow, as emotional states also influence people in their planning or project management activities, e.g., regarding risk preferences (Table 1). In the context of emotions and affects, visual aesthetics play a key role (Bennett et al. 2007; Cawthon and Moere 2007). The physical visualization of information and data goes one step further, activating not only visual but also, for example, haptic senses to evaluate information, meanings, and messages (Bürigi and Roos 2003; Djavaherpour et al. 2021; Müller et al. 2022; Roos et al. 2004). For example, the representation of consecutive accident-free days with physical entities may have a greater impact on worker behavior than a sheer number. Similarly, the physical visualization of sustainability goals and achievements may have a positive impact on behavior.*

In addition, visualizations in the form of comparisons between manufacturing groups can trigger positive competition.

Proposition 6: Methodological variety and rigor *Overall, we see a variety of methods used to study and design visualizations for manufacturing and operations management, with engineering approaches clearly dominating (Figure 6). However, studies that rigorously apply multiple methods to collect both qualitative and quantitative data for triangulation are sparse. Notable exceptions include Stowasser (2006) and Zhang (1998). Thus, we see room for improvement in the application of social science methods. In addition, physiological measurements such as eye tracking (Holmqvist et al. 2023) have not yet been widely used but would be useful in the InfoVis domain. Regarding the operationalization and measurement of e.g., the value of visualizations (Fekete et al. 2008; van Wijk 2005; Wang et al. 2019), we consider measuring the ability of visual means to mitigate behavioral biases and thus improve economic decision making, as addressed in this work, as very promising.*

Proposition 7: Bold visualizations and storytelling *The studies in the top manufacturing and operations management outlets examined in this paper do not yet reflect the wide range of visualization possibilities that exist in the InfoVis domain (Keck et al. 2020, 2021). This is also true for efforts to convey messages through visualizations, not just through a single visualization (or dashboard) that inherits as much information as possible, but through storytelling using multiple sequential and linked visualizations. Thus, we see the design and especially the systematic evaluation of innovative visualizations as another promising approach to transfer to the BOM.*

Proposition 8: AI and visualizations *Automation and AI are becoming increasingly important in operations management decision making (Hoberg and Imdahl 2023). However, in our literature sample, only Yoo and Kang (2021) explicitly considered visualizations to increase the transparency or eXplainability of AI (XAI). Nevertheless, visualizations should also be considered as a relevant companion for AI and XAI in operations management to increase trust and acceptance in the algorithms and results (Beauxis-Aussalet et al. 2021). Interactive visualizations in particular can play a significant role here.*

5.2.2 Proposition for interventions and testable hypotheses about visual means in behavioral operations

Based on the identified links in our study between behavioral operations and visual means through behavioral mechanisms,

we eventually propose a conceptual map linking these concepts (Table 17.). It is meant to allow to derive more concrete streams of (empirical) investigations in form of (testable) hypotheses. To present how to read and use this map as starting point for further research and development, we also propose an exemplary hypothesis. Common methods of BOM may be reasonable to be applied like laboratory and field experiments or surveys (Bendoly et al. 2010).

Hypothesis (Highlighted in grey in Table 17.): Shifting the visual reference point in inventory management decision influences reference dependence bias. Inventory decisions, such as those in the newsvendor model, are influenced by the decision maker's mental anchors or reference points on which he or she bases the decision. Often these anchors are the mean demand or the previous demand realization (Schweitzer and Cachon 2000). By supporting the description of the decision problem with visual means that actively shift the mental reference points to a superior one, the economic decision could be improved. The salience of the new anchor can be achieved, for example, by using a distinct color or shape (MacEachren et al. 2012; Moody 2009).

6 Conclusions

In our work, we systematically investigated and reviewed the coverage of visualizations in the P&OM literature with applications in manufacturing, respectively in 64 articles published in scholarly journals. Among these papers, we identified eight operational contexts and eight archetypical visualization clusters that are designed, applied, and evaluated in these contexts (Table 7). Furthermore, we identified areas of higher (e.g., visualizations of CAD data in product development) and lower scientific coverage (e.g., in SCM) and described our findings using indicative papers along the eight operational contexts. Thereby, we specifically focused on behavioral mechanisms and outcomes when using visualizations in manufacturing operations. Our overall findings were synthesized along our CIMO review framework (Fig. 8) and the conceptual framework integrating and depicting specifically the relations between BOM and InfoVis (Tables 8, 9, 10, 11, 12, 13, 14, 15, and 16).

We thus derive, that the more abstract, uncertain, or non-deterministic the operations contexts and outcomes are (like strategic planning in entrepreneurial or organizational contexts), the more pictorial visualizations (images, icons, signs) are used and assessed, but also the more psychological aspects are considered. However, this is also true for more deterministic and attentive tasks and purposes like shop floor and visual management. I.e., either for generating mental images in decision-makers to foster innovative or visionary

Table 17 Linking behavioral mechanisms with operations management contexts and visual means (based on Lindner et al. 2022b)

		Behavioral mechanism											
		Risk preference	Bounded rationality	Cognitive reflection	Judgment bias	Reference dependency	Over-confidence	Mental accounting	Cognitive dissonance	Endowment effect	Cognitive appraisal	Collaboration / coordination	Information sharing
Operational context	Contracting	•										•	•
	Inventory management	•	•	•	•	•	•	•					
	Supply chain management											•	•
	Procurement and auctions	•							•			•	•
	Service operations		•	•									
	Revenue management	•			•								
	Forecasting				•	•	•						
	Quality management		•						•				
	Capacity management		•										
	New product development	•	•					•		•		•	•
	Production management	•		•									
	Process improvement		•						•		•		
Visual mean (intervention)	Visual salience	•		•		•							
	Visual reference point	•		•		•							
	Visualizing uncertainty/risk	•		•			•						
	Recall		•	•		•	•						
	Comparisons				•	•	•						
	Sequencing					•				•			
	Shared mental models											•	
	Different perspectives		•	•	•								
	Aesthetics	•						•	•	•	•		

Note. The shaded parts exemplarily highlight the links (intersections) between an operational context (inventory management), an observed behavioral mechanism (reference dependency), and a visual intervention (visual reference point)

behavior or for short-term signaling purposes on the shop floor to trigger certain behavior, pictorial visuals are preferred to texts or numbers. On the other hand, the more engineering activities are involved and the more realistic virtual representations of real-world physical objects are needed—as in product development and design, or manufacturing layout—the more focus is on (information) technological and computational aspects than on human factors—e.g. when

using CAX or AR/VR. Exceptions are when human workers are to be modeled, like in ergonomics, or when virtual objects are used to train and educate people. In these cases, human factors are also considered in designing and applying the visualizations.

Nevertheless, articles considering in detail human factors or perceptual, cognitive, and behavioral aspects in InfoVis applications in P&OM are a minority. Furthermore, the literature often

lacks a solid theoretical foundation in behavioral models, and/or the interventions, mechanisms, and outcomes are not systematically assessed and evaluated—although positive exceptions exist. However, compared to the general BOM and InfoVis literature, we argue, that the potentials of different visualizations and visual means in P&OM and especially in BOM contexts to support human cognition as well as behavior and decision-making are not yet fully exploited. Furthermore, the stream of research on visualization in (behavioral) manufacturing operations seems to lack continuous efforts and follows two parallel paths using different visualizations and methodologies, depending on either engineering or management related activities.

Thus, we proposed eight directions for further research and development to this regard and a conceptual map linking behavioral operation contexts with visual means through their shared behavioral mechanisms to derive concrete starting points and (testable) hypotheses (Table 17.).

6.1 Limitations

However, we see also limitations of our research approach, mainly inherent to the review protocol. First, as we neglected the explicit inclusion of “graphs” in the search phrases and as we focused specifically on InfoVis applications in discrete manufacturing contexts, we expect to find further and maybe different research in even broader OM contexts, such as in the process industry. Second, we searched P&OM literature published only in journals with certain ratings in scientific management rankings. As the topic of InfoVis in P&OM and BOM seems to have not yet been extensively covered, many approaches to this field might not yet have made their way into the top-tier journals but could also provide promising insights and bolder or more avant-garde approaches. And finally, we excluded the literature that is not dealing exclusively with InfoVis. Further literature, especially on DSS, might consider visualizations as a part of a greater decision-making and reasoning process as well as information systems with more complex contexts and requirements. This could also be a reason why, e.g., surprisingly no map-based visualizations in SCM and logistics contexts appeared in our literature sample, although geospatial networks (Schöttler et al. 2021) or visualizations for SCM (Lou et al. 2020) are subjects of recent research in this field.

6.2 Contributions to theory and practice

We are confident to contribute with our work to the emerging research and discussion on visualizations in P&OM

(Basole et al. 2021; Jin 2022; Shneiderman 2021; Tanaka et al. 2022), and especially in BOM, by integrating the body of knowledge of both fields, to give an overview, encourage peers and propose first guidance to dedicate themselves to the promising investigation of InfoVis in P&OM and BOM, as well. Considering IIoT, AI, and I5.0 (Breque et al. 2021; Huchzermeier et al. 2022; Xu et al. 2021), visualizations will play a vital role in XAI and improved HCI for manufacturing operations (Beauxis-Aussalet et al. 2021; Hoberg and Imdahl 2023; Karran et al. 2022; Lindner and Reiner 2023).

We first provided new theoretical links between behavioral biases in operations and the respective benefits and pitfalls of visualizations (Table 1) and were the first to address RQs 1–2, which is our original contribution to the field. We extended existing frameworks on visualizations in management by integrating and extending them with the specific distinction between behavioral (cognitive, social, and emotional) and visual mechanisms (Table 2).

The subsequent transparent analysis of the literature systematically reveals the underlying mechanisms between visualizations and (behavioral) operations and helps to understand how and why certain visual means are used to achieve operational purposes (Tables 8, 9, 10, 11, 12, 13, 14, 15, and 16; Fig. 8). It also allows the identification of research gaps and the development of further research questions or even hypotheses for other researchers to contribute to the field. Our own contribution to this academic endeavor is eight propositions that highlight promising avenues of further investigation to advance the field. Finally, Table 17. allows for the concrete derivation of research questions and (testable) hypotheses as a starting point.

For practitioners such as visualization and DSS designers, but also domain experts and operations managers, Tables 8, 9, 10, 11, 12, 13, 14, 15, and 16, Fig. 8, and Table 17. provide insights and starting points for immediate action. First, the description and explanation of mechanisms for the different operational contexts can help to reflect on one's own design and use of visualizations with respect to biases that could be enhanced or mitigated (Table 1). The extensive description of visual means in (other) operational clusters and Fig. 8 allows practitioners to search for similar or more appropriate visualizations to apply and test, moving from standard visualizations to more targeted ones. Finally, Table 17. offers also concrete starting points for critically reflecting on existing applications of visualizations in terms of economic biases and the possibility of modifying managerial interventions accordingly. We hope that this will be a useful addition to the manager's toolbox.

Appendix

Table 18 Characteristics of this work and similar literature studies concerning visualizations in manufacturing and production management

Characteristic	Sackett et al. (2006)	Ramanujan et al. (2017)	Zhou et al. (2019)	Lou et al. (2020)	Wang et al. (2022)	This Study
Discipline	Manufacturing (Management)	Manufacturing	Computer Science/Manufacturing	Computer Science/Supply Chain Management	Computer Science/Manufacturing	Manufacturing/Behavioral Operations (Management)
Scope	Visualizations for manufacturing sequence management	Visualizations for sustainable lifecycle design	Visualizations for smart manufacturing	Visualizations for supply chain management	Visualizations of multimedia data for manufacturing	Visualizations for manufacturing operations concerning behavioral factors
Search protocol	Not explicated	Keyword search in six databases	Manual scanning of specific venues and selective keyword search in Google Scholar	Keyword search in Google Scholar ^a	Keyword search in specific venues	Keyword search in two databases ^b
Quality criteria	Not explicated	Indexed in at least one of the selected academic databases	Published in one of the selected major visualization venues	Published in peer-reviewed and/or top-ranked venue ^c	Published in venues with high recognition	Published in ranked journals ^d and indexed in at least one of the selected academic databases
No. of articles	83 ^e	164	53	14	61	64
Time span	1972–2004 ^f	1985–2017	2001–2018 ^g	2003–2020 ^f	2009–2022	1997–2023
Classification	Linking functional requirements with visualization requirements, visualization techniques and applications	Categorization according to six lifecycle stages	Positioning literature according to application scenarios (replacement and creation) and industry sectors	Organizing literature in eight topics ^h	Classification according to manufacturing multimedia types, visualization techniques, interactive analysis methods and application areas	Classifying the literature according to the type of visualization, operational context as well as considered behavioral and performance factors

^aFollowing the PRISMA methodology (Moher et al. 2009). ^bFollowing the CIMO logic (Denyer and Tranfield 2009). ^cNot further specified. ^dRanked at least C/D in the German VHB-JOUR-QUAL3 (2015), 2 in the British AJG (2018) or 3 in the French CNRS (2019)—i.e., omitting the lowest rank each. ^eOverall number of referenced articles due to lack of explication. ^fOverall time span of referenced articles due to lack of explication. ^gTime span of 36 as representative explicated articles by the authors. ^hUsing content analysis according to Bengtsson (2016)

Table 19 Overview of the assessed literature, assigned categories, and dimensions

ID	Reference	Operational Context ^a										Type of Visualization ^b										Behavioral/ Performance ^c					Research Approach ^d									
		PD	ML	PP	PC	SF	SC	ET	OS	IF	GN	FC	HT	2D	3D	CAX	AR/VR	S	C	E	P	CS	AB	En	Ex	CA	LR	AM	Sy	Co						
1	Afanasiev et al. (2020)			✓	✓								✓					✓	✓	✓								✓			✓	✓				
2	Bengtsson et al. (1997)	✓	✓												✓			✓	✓	✓			✓		✓							✓				
3	Bi et al. (2016)			✓									✓	✓				✓	✓	✓			✓		✓											
4	Bititci et al. (2016)							✓	✓			✓	✓					✓	✓	✓			✓													
5	Chen et al. (2011)	✓						✓				✓						✓	✓	✓			✓													
6	Chen et al. (2013)			✓									✓					✓	✓	✓			✓													
7	Choi and Samavedam (2002)	✓												✓			✓	✓	✓	✓			✓													
8	Chung and Peng (2008)	✓													✓				✓				✓													
9	Egger and Masood (2020) ^e					✓										✓		✓	✓	✓												✓				
10	Eppler and Platts (2009)							✓	✓	✓	✓	✓	✓	✓				✓	✓	✓			✓													
11	Fernandes et al. (2003)							✓							✓			✓	✓	✓			✓		✓											
12	Førsund et al. (2009)			✓									✓					✓	✓	✓												✓				
13	Hou and Pai (2009)							✓					✓					✓	✓	✓			✓		✓											
14	Huang et al. (2015)	✓														✓		✓	✓	✓			✓		✓											
15	Hvam and Ladeby (2007)	✓								✓						✓		✓	✓	✓				✓												
16	Iyer et al. (2001)			✓											✓									✓												
17	Keivanpour and Ait Kadi (2018)	✓										✓	✓					✓	✓				✓													
18	Kim et al. (2015)	✓													✓				✓	✓			✓													
19	Kim et al. (2006)	✓		✓															✓	✓				✓												
20	Kumar et al. (2007)	✓											✓							✓			✓													
21	Kurpiuweit et al. (2019)					✓			✓									✓	✓	✓																
22	Lämkull et al. (2007)	✓													✓			✓	✓	✓				✓								✓				
23	Latham and Tello (2016)							✓	✓			✓						✓	✓	✓																
24	Lee et al. (2011a)	✓							✓		✓	✓	✓					✓					✓									✓				
25	Lee et al. (2011b)	✓		✓					✓						✓			✓	✓					✓		✓						✓				
26	Lee and Hong (2016)													✓				✓																		
27	Lee and Kim (2017)	✓		✓														✓	✓				✓													
28	Li et al. (2018)	✓		✓														✓		✓				✓								✓				
29	Lindskog et al. (2017)	✓																✓	✓	✓				✓												

Table 19 (continued)

IID	Reference	Operational Context ^a										Type of Visualization ^b							Behavioral/ Performance ^c				Research Approach ^d									
		PD	ML	PP	PC	SF	SC	ET	OS	IF	GN	FC	HT	2D	3D	CAX	AR/VR	S	C	E	P	CS	AB	En	Ex	CA	LR	AM	Sy	Co		
30	Marino et al. (2021)					✓									✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓						
31	Nakamura et al. (2011)				✓								✓					✓	✓							✓				✓		
32	Nottingham et al. (2001)				✓								✓					✓	✓					✓								
33	Parush et al. (2007)						✓					✓						✓	✓					✓								
34	Patel et al. (2006)	✓													✓			✓	✓				✓		✓							
35	Rejeb et al. (2021) ^e						✓								✓			✓	✓								✓					
36	Rose (1998)	✓		✓								✓						✓	✓				✓									
37	Sackett et al. (2006) ^f	✓		✓		✓												✓	✓								✓					
38	Salah et al. (2019)							✓							✓			✓	✓						✓							
39	Seider (2006)								✓				✓					✓	✓						✓							
40	Skarlo (1999)			✓														✓	✓						✓						✓	
41	Song et al. (2009)	✓													✓			✓							✓							
42	Stadnicka and Ratnayake (2017)		✓						✓									✓	✓				✓									
43	Stowasser (2006)			✓						✓						✓		✓	✓						✓							
44	Sun and Kuo (2002)			✓								✓						✓	✓							✓						✓
45	Wang and Li (2006)														✓			✓	✓					✓								
46	Yap et al. (2003)	✓														✓		✓	✓													
47	Zhang (1998)			✓									✓			✓		✓	✓					✓		✓					✓	
48	Zhang et al. (2004)	✓													✓			✓	✓					✓		✓					✓	
49	Zülch and Stowasser (2002)			✓					✓					✓				✓	✓						✓							
50	Canonico et al. (2022)	✓							✓			✓						✓	✓													
51	Corallo et al. (2022)	✓													✓			✓	✓													
52	Ferreira et al. (2023)																	✓	✓													
53	Ghadge et al. (2022)						✓						✓					✓	✓													
54	Hoffmann et al. (2023)			✓													✓	✓	✓												✓	
55	Krajčović et al. (2022)							✓										✓	✓													✓
56	Li et al. (2023)			✓										✓				✓	✓													
57	Mia et al. (2023)			✓														✓	✓					✓								
58	Moerchel et al. (2022)	✓								✓								✓	✓													
59	Moro et al. (2022)										✓							✓	✓													
60	Tainaka et al. (2023)		✓														✓	✓	✓													✓

Table 19 (continued)

ID	Reference	Operational Context ^a										Type of Visualization ^b							Behavioral/Performance ^c					Research Approach ^d									
		PD	ML	PP	PC	SF	SC	ET	OS	IF	GN	FC	HT	2D	3D	CAX	AR/VR	S	C	E	P	CS	AB	En	Ex	CA	LR	AM	Sy	Co			
61	Vernica et al. (2023)	✓											✓		✓		✓	✓					✓										
62	Yoo and Kang (2021)	✓													✓			✓			✓		✓										
63	Zhang et al. (2022)		✓													✓		✓				✓		✓									
64	Zhou et al. (2021)			✓												✓		✓									✓						
Sum		22	11	14	11	5	5	5	8	10	3	10	10	21	4	22	15	24	52	17	41	18	16	25	12	15	5	6	4	3			

^aPD product development, ML manufacturing layout, PP production planning, PC production control, SF shop floor management, SC supply chain management, ET education and training, OS organizational and strategic; ^bIF images and figurative, GN graphs and networks, FC flow charts, HT hierarchies and tables, 2D 2-dimensional, 3D 3-dimensional, CAX computer-aided X, AR/VR augmented and virtual reality; ^cS social, C cognitive, E emotional, P performance; ^dCS case study, AB action-based research, En engineering approach, Ex experiment, CA conceptual approach, LR literature review, AM analytical model, Sy survey, Co computational (Table 5)

^eLiterature review (partially covering several contexts). ^fLiterature review focusing on visualization functionalities rather than types of display as in this table. It is therefore not mapped to specific visualizations here

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Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

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