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DOI
10.1016/j.aei.2025.103557

Publication date
2025

Document Version
Final published version

Published in
Advanced Engineering Informatics

Advanced Engineering Informatics 67 (2025) 103557

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

Full length article

Enhancing Situation Awareness of Construction Managers using Human-centered Digital Twins

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ARTICLE INFO

Keywords:
Situation Awareness
Digital Twin
Construction Management
Human-Data Interaction
Offsite Construction
Goal-Directed Task Analysis

ABSTRACT

As the construction industry increasingly adopts digital technologies, recent studies emphasize digital twins as essential tools for managing construction projects and automating workflows. Although research has advanced the technical aspects of digital twins, there is a notable gap in examining human performance factors, particularly situation awareness – a cognitive process crucial for recognizing, comprehending, and anticipating changes in the work environment. With greater reliance on automation, neglecting this critical capability can lead to severe oversights, particularly during disruptions. To address this gap, we conducted a qualitative study grounded in a theoretical framework to explore the situation awareness requirements under different disruption scenarios in two contrasting construction contexts: offsite production and onsite assembly. First, drawing on 16 semi-structured interviews and non-participant field observations, we employ goal-directed task analysis to reveal the distinct information needs in each context. Second, through a comprehensive content analysis of the interview narratives, we identify the dynamics of gaining and maintaining situation awareness and provide digital twin design recommendations. Findings indicate that managers must shift from a macro-level overview to a micro-level detail in offsite production, requiring digital twin displays with adaptable granularity. In contrast, onsite assembly demands an intensely iterative approach to situational awareness, which calls for comprehensive real-time digital twin displays that support quick back-and-forth assessments. This study contributes by formalizing experts' background knowledge, which can serve as a valuable basis for creating context-sensitive digital twin systems that better support human decision-making in offsite construction contexts and beyond.

1. Introduction

In recent years, the construction industry has been progressively adopting digital technologies, marked by growing automation and connectivity, with the digital twin (DT) concept playing a pivotal role in driving innovation. DTs serve as virtual counterparts to physical assets or systems [1], enabling professionals to consolidate vast information streams to address the growing complexity of modern projects [2]. Proposed application scenarios include offsite production scheduling [3], tracing materials [4], improving onsite assembly [5] and progress monitoring [6]. These applications illustrate the transformative influence of DTs across different stages of construction.

Current research on DTs in the construction industry emphasizes integrating physical and virtual domains through a technical lens [7,8]. Studies focus on advancements in virtual modeling, data acquisition, semantic interoperability and scheduling [9–12]. Other researchers extensively explore computer vision for real-time monitoring and project tracking [13,14], as well as the fusion of DTs with artificial intelligence (AI) for improved project management [15,16]. The resulting DTs are inherently complex systems, integrating diverse network technologies, sensors, embedded systems, computational models, and human-data interfaces to create a cohesive virtual representation of physical assets and construction processes [17]. As such, they demand considerable financial resources and development efforts.

However, successfully adopting DTs in real-world settings requires addressing human-related challenges beyond technological sophistication [18–20]. Studies highlight that construction managers (especially more experienced ones) tend to resist digital technology adoption due to its disruptive impact on established workflows [21,22]. While DTs provide vast amounts of data, they can become counterproductive if

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https://doi.org/10.1016/j.aei.2025.103557
Received 24 February 2025; Received in revised form 30 April 2025; Accepted 9 June 2025
Available online 20 June 2025

they overwhelm users with irrelevant information or introduce complex navigation patterns that do not match intuitive mental models and cognitive resources [23]. Besides, over-reliance on data output might lead to automation bias [24], whereas under-confidence in system accuracy can produce unwarranted mistrust [25]. As such, DT solutions must be aligned with managerial workflows to ensure that human operators can effectively comprehend and address pressing disruptions. Information visualization within DTs must be human-centered so that users can effectively interpret critical data. Therefore, a nuanced understanding of the interplay between DT capabilities and the cognitive processes of the professionals who will operate these tools in practice remains essential to maximize DT utility.

Building on these considerations, situation awareness (SA) emerges as a potential lens for understanding how managers assess demanding situations in uncertain environments. SA refers to an individual's perception of environmental elements, comprehension of meaning, and projection of their future status [26]. SA is integral to managing dynamic systems like construction projects [27]. Here, SA is not only about sensing but also about structuring knowledge so that managers can rapidly interpret key signals. In the face of intense project disruptions – from unexpected supply delays to unforeseen weather events [28] – robust SA is important for construction managers aiming to ensure the project proceeds as planned despite these uncertainties. In construction, the SA requirements, i.e., the data individuals need and they way they process it mentally for a particular decision, often differ from those in other industries [29–31], demanding careful alignment of explicitly represented information with the construction project's stage and complexity.

Despite the promise of DTs for real-time insights into complex construction processes, there is a lack of knowledge about how these systems should be designed to enhance and not impede SA in the face of project disruptions. Previous research indicates that DTs have the potential to improve operators' SA by offering timely, contextualized data [32]. At the same time, high volumes of incoming information and poorly designed interfaces can cause cognitive overload or uncertainty if they do not align with users' mental models [33]. While studies in our field increasingly cite SA as a goal of DT applications [15,17,34] their analyses seldom clarify how these tools directly strengthen (or potentially undermine) managers' capacity to interpret disruptions accurately. We cannot precisely define the threshold at which the DT shifts from a beneficial tool for human performance to one that fosters automation bias or mistrust due to information overload or compromised data quality. Simultaneously, theoretical investigations of SA frameworks in construction [27,35] stop short of converting the identified SA requirements and the dynamics of gaining and maintaining SA into actionable design principles for emerging DT systems. Bridging this gap between technological advancements and human-centered SA needs is essential for developing a DT paradigm that leverages the richness of real-time data while protecting managers from cognitive overload during critical project disruptions.

To address this gap, we present a qualitative analysis that links DT functionalities with improved SA for construction management, centering on three fundamental research questions. RQ 1 – *What are the key situation awareness requirements for managers investigating disruptions across different construction project phases?* clarifies how decision-makers process and interpret critical data under selected unpredictable conditions. RQ 2 – *How do varying work environments (e.g., factory-based vs. onsite) shape managers' strategies to build and maintain situation awareness under disruptive conditions?* highlights how environmental complexities influence the depth and breadth of awareness needed to investigate disruptions. RQ 3 – *How can human-centered digital twins be designed to meet the distinct situation awareness requirements that emerge in these varied construction contexts?* moves the discussion toward tangible IT solutions, emphasizing how DTs can be refined to enhance managerial cognition genuinely. We adopt a qualitative approach for knowledge elicitation because it reveals the nuanced ways managers obtain knowledge in high-stakes scenarios, offering contextual depth that quantitative measures alone might overlook. Ultimately, we aim to bridge the gap between theoretical SA frameworks and the technology-driven DT research in construction. The resulting insights promise to inform new design guidelines and best practices, paving the way for DT solutions that enable construction professionals to respond to disruptions more efficiently.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature, focusing on DTs in construction management, human-DT interaction, and the SA framework of Endsley [36] alongside its role in construction management. Section 3 describes the research methodology, including using semi-structured interviews alongside non-participant observations and applying Goal-Directed Task Analysis (GDTA) to uncover the cognitive requirements of construction managers. Section 4 presents the study's findings, emphasizing the contrasting SA requirements of offsite production and onsite assembly. For each construction context, we uncover three unique cognitive patterns that characterize the processes of acquiring and maintaining SA, and we propose three targeted design recommendations for DTs to address these nuances. Section 5 discusses the findings and their broader implications for theory and practice while offering insights into human-centered design strategies for DTs. Finally, section 6 concludes the study and outlines future research directions.

2. Literature review

2.1. Digital twins for construction management

A DT is a digital representation that mirrors physical entities, such as objects, systems, or processes, designed to serve specific functions [1]. The concept of twinning involves a bi-directional connection: data flows from the physical to the virtual domain and vice versa. The fundamental building blocks of DTs consist of the physical entity, its digital counterpart, and the interactions occurring within their physical and virtual environments [37]. The frequency, accuracy, and scope of twinning vary across industries and depend on the specific application. By consolidating diverse information streams, DTs can enhance human operators' ability to comprehend and address complex challenges [2].

The vision for DTs in construction management lies in achieving robust, integrated systems that optimize project workflows through advanced, data-driven analyses [38,39]. DTs should be understood not as standalone technologies but as integral digital innovations that enhance and elevate existing management practices. For example, by digitally augmenting conventional lean management tools such as visual management and value stream mapping [40], DTs substantially improve communication, visibility, and the flow of information, which are critical for efficient production management [15,41–43]. Beyond simply augmenting traditional tools, DTs introduce powerful analytical capabilities, including real-time integration of diverse data sets, predictive modeling to identify waste early, and automated generation of recommendations for corrective actions [30,41,43]. Consequently, DTs extend beyond the limitations of conventional methods by uncovering hidden correlations and proactively addressing potential disruptions, thus adding substantial value to the management of complex production processes.

Research on DTs in the construction industry primarily focuses on developing sophisticated technological solutions for integrating the physical and virtual project realms [8]. This includes advancements in data acquisition, transmission, virtual modeling, and semantic interoperability of models and algorithms driven by engineering and computer science expertise [9,10,44]. The resulting DTs are inherently complex systems, integrating diverse network technologies, sensors, embedded systems, computational models, and human-data interfaces to create a cohesive virtual representation of physical assets and processes [17]. As such, they pose a significant investment in financial resources and development efforts. Establishing clear and precise design requirements ensures the system is purpose-built to meet the intended objectives [45,46].

Aligned with this technology-centered approach, studies investigating development requirements and providing design guidelines for DTs in construction contexts strongly emphasize technical aspects. For instance, Boje *et al.* [9] categorize DT requirements into procedural, technological, modular, and interconnectivity. Their framework emphasizes technical priorities such as sensor placement, cost-benefit analyses, data integration, data security, and system modularity. Their focus on interconnectivity – linking individual DTs with other systems and enabling multi-level communication – centers on system functionality rather than user experience or usability for construction professionals. Kosse, Hagedorn and König [47] elaborate on requirements for DTs, identifying technical, process-oriented, spatial-structural, and life cycle-oriented dimensions. As part of the extensive *BIM2TWIN* research project, DT requirements emerged from case studies emphasizing data modeling for quality, equipment, operation, and safety, focusing on planned versus actual progress [34,48]. Borrmann *et al.* [10] emphasize data management, advocating for object-oriented modeling to handle the complexity of construction projects.

2.2. Human-digital twin interaction in construction management

Successful adoption of DTs and the utility of the underlying computational methods will require more than technological sophistication; widespread industry acceptance depends on addressing practical, human-centric challenges [18]. Decades of research into the impact of automation on human workers have shown that human factors significantly influence the effectiveness of new IT systems [25]. Studies highlight that construction managers often resist digital technology adoption due to its disruptive impact on established workflows [22,49]. Adopting DTs in construction is no exception, and the human dimension remains a critical challenge [49,50].

The integration of the human factor in DTs has only recently gained significant attention. The primary focus is the division of roles between human agents and DTs, following the idea that human operators and DTs form an integrated team, each relying on the other for effective functioning [51]. Agrawal *et al.* [52] propose a two-dimensional framework to distribute responsibilities between humans and DTs. By conducting case study interviews, the authors identify varying levels of automation that DTs can adopt for tasks such as observation, evaluation, decision-making, and execution during construction activities. Given the diverse role distributions, they stress the importance of developing tailored interfaces to facilitate interaction between humans and DTs. Abdelmegid *et al.* [53] introduce an integrated framework that connects socio-technical dimensions with the DT maturity levels – digital model, digital shadow, and DT – based on Kritzinger's [54] classification. Although these two studies advance scientific discourse toward human-related considerations, their focus remains narrow, addressing only selected aspects of human-DT interaction, such as role distribution and task automation. Merely assigning specific roles within the human-DT team does not ensure their successful operation [55]. A recent study by Soman *et al.* [17] investigating human-DT interfaces proposes using collaborative control rooms during construction projects. The researchers integrate comprehensive data from multiple sources, employ predictive analytics simulations, and utilize large interactive displays to convey extensive real-time information. Their case study validation resulted in shorter and more productive weekly look-ahead meetings of the construction team. While reduced meeting durations hint at a positive influence, it remains unclear how each element of the DT impacts the managers' day-to-day comprehension of the current physical site environment and project status. There is a temptation to assume that simply adding more data, intensifying data analysis, and employing additional predictive algorithms will continuously elevate the effectiveness of managers. However, this notion was already challenged in the 90 s and noted that human factors must be accounted for [56,57].

A more detailed understanding of how DTs influence specific cognitive functions is crucial. Recent research is pioneering computational methods to harness and process vast streams of automated data, integrating these outputs into the work of construction managers [58]. As such streams of automated data outputs become integral to managerial tasks, the risk of overwhelming cognitive capacity increases, potentially leading to misinterpretations or excessive reactions [23]. This is especially critical in the construction industry, where dynamic project timelines, uncertain supply chains and many risk factors increase the need for well-structured digital systems tailored to these complex environments [59]. By identifying the variables that influence human-DT interaction and embedding them in a contextually relevant framework, DTs can better align with cognitive needs to maximize their utility and robustness [19].

2.3. Situation awareness for managerial decision-making

Since direct observation of a manager's cognitive processes during tasks is not feasible, the concept of SA provides a means to infer and understand these interactions [60]. According to the widely acknowledged Endsley model, SA is "*the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future*" [36]. The model can be used to understand how human operators monitor swiftly changing situations, process real-time task-relevant information provided by digital artifacts and make immediate decisions to fulfill certain goals [61,62]. Unlike static knowledge, such as system rules or business procedures, SA prioritizes real-time domain-specific data [26].

In Endley's model [36], SA is conceptualized in three hierarchical levels (see Fig. 1):

- Level 1 – *Perception*: Recognizing and gathering information about the current situation.
- Level 2 – *Comprehension*: Understanding the significance of the perceived information.
- Level 3 – *Projection*: Predicting future states and outcomes based on comprehension.

These cognitive processes are influenced by task / system factors like workload, interface design, and automation, as depicted at the top of Fig. 1. They are also influenced by individual factors like goals & objectives, memory structures and information processing mechanisms, as shown at the bottom of Fig. 1. These individual factors are deeply rooted in cognitive psychology [63,64]. In practice, SA reflects the interaction between these two layers: If either the system or the human side changes, the resulting SA will also change.

Although Endsley's model's basic form can be retained across industries, research on SA must be tailored to specific domains and individuals involved [29,30]. SA has been investigated in the fields of aviation [67], emergency response [68], maritime navigation [29], flexible manufacturing [63], human-robot collaboration [69] and construction projects [70], making it particularly relevant to this study. Across these domains, task / system factors vary significantly: Aviation involves high-speed automation and cockpit interfaces; manufacturing emphasizes routine operations and machine reliability; construction faces dynamic sites, unpredictable sequencing and spatial complexity. Meanwhile, individual factors differ between professionals within a particular professional domain: A novice manager, for instance, may process information very differently than an experienced one.

SA is strongly related to the theoretical foundations of naturalistic decision-making – a research paradigm developed explicitly to understand and support decision-making in real-world settings instead of controlled laboratory experiments [64]. Unlike traditional decision theories that outline structured processes of option evaluation, naturalistic decision-making investigates how practitioners cope with ill-defined problems, intense time pressures, and complex

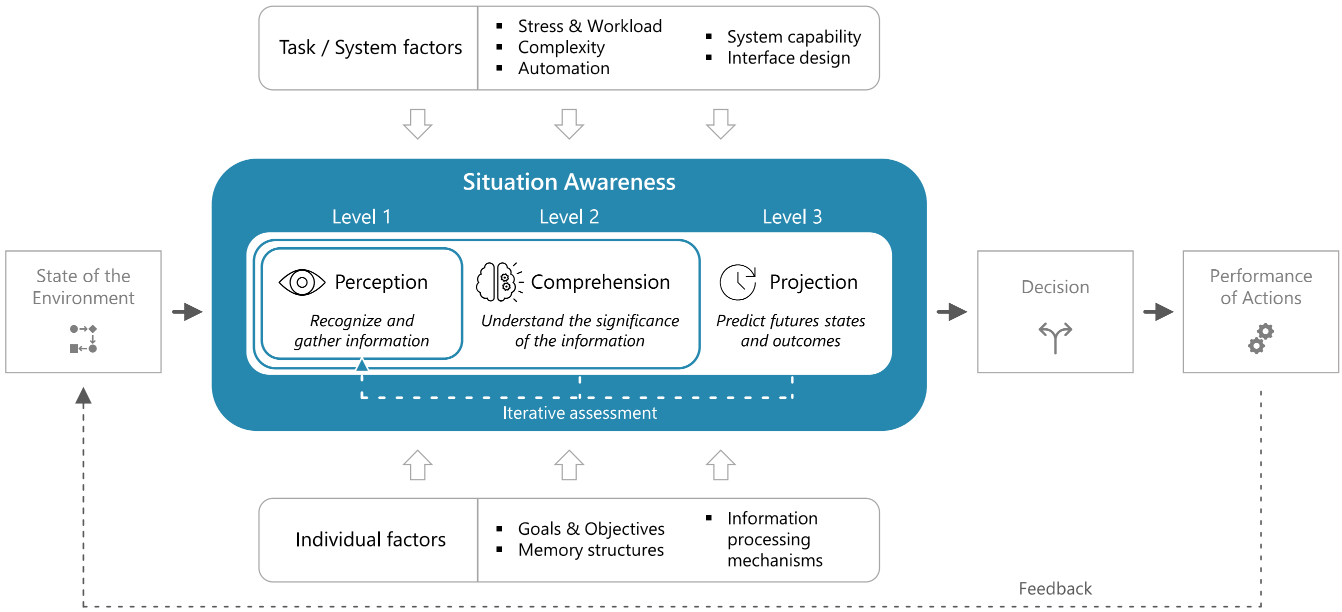

Fig. 1. Model of SA in dynamic decision-making, adapted from Endsley [36,63].

interdependencies, which are conditions frequently mirrored in the construction domain [71]. SA should not be mistaken for generating, selecting or implementing options for addressing a situation [72]. Instead, SA feeds into decision-action cycles as a crucial input for individuals overseeing dynamic systems, enabling effective adaptation to evolving scenarios [67,73]. The SA model provides a robust explanatory framework for problem identification and sensemaking – two pivotal cognitive processes in human problem-solving [64]. Researchers have proposed other concepts, notably Klein's Recognition-Primed Decision model [74], which emphasizes the role of pattern recognition in expert decision-making, and the Data-Frame Theory [75], which describes how mental frames are developed and adapted. Weick's view of organizational sensemaking further introduces a sociocultural perspective on how groups negotiate meaning in uncertain environments [76,77]. In cognitive sciences, more broadly, there is still debate over which concept best captures the complexities of human cognition [64,75]. Nonetheless, a lengthy analysis of these theoretical differences is beyond the scope of this study.

2.4. *Situation awareness in construction management*

In construction management, efforts to characterize SA and define its requirements continue to gain momentum. Akinci [78] was among the first to consider SA during construction and facility operations, emphasizing the importance of delivering accurate information promptly. Kärkkäinen *et al.* [79] propose a conceptual model called *situation pictures* to understand the unique characteristics of construction and production management. They emphasize that the contrasting nature of offsite production and onsite assembly environments demands more adaptive supply chain strategies, particularly regarding timely and accurate information flow. Lavikka *et al.* [80] explore high-level data flows and digital situation pictures within offsite supply chains, shedding a conceptual light on how SA might be leveraged beyond the job site. Investigating the Finnish construction industry, Lappalainen *et al.* [81] find that current digital SA systems are primarily limited to supporting level 1 (perception), indicating that most systems capture only basic information without offering deeper analysis or decision support. Furthering this research, Lappalainen *et al.* [82] evaluate subject matter experts' perspectives on SA in infrastructure projects, highlighting ongoing challenges in balancing the quality of SA data with human validation and suggesting a need to investigate the specific SA requirements of site personnel. Assessing SA concerning takt production on the site, Halttula and Seppänen [83] emphasize its potential benefits but did not clearly define specific SA requirements. Similarly, Martinez *et al.* [70] use a serious game-based analysis to examine how a lack of SA affects production planning and onsite decision-making, finding that insufficient information hampers site managers' ability to manage uncertainties, yet without detailing the crucial information needed. The study by Pillajo, Mourgues and González [31] provides a pioneering and comprehensive application of GDTA to formalize the SA requirements of field managers during indoor construction activities. It bridges theoretical SA principles with practical challenges, offering detailed insights into the numerous goals, decisions, and information managers need to understand the current situation.

2.5. *Situation awareness-aligned information technology*

Technological advancements offer new possibilities to strengthen SA yet require careful consideration of the users' cognitive processes. On the one hand, IT systems represent a system factor in Endsley's model (see Fig. 1) that enhances workers' SA by automatically collecting and processing relevant data. Research from other domains highlights the benefits of DTs in augmenting human operators' SA. For instance, Eckhart, Ekelhart and Weippl [84] present a DT-based SA framework that offers a comprehensive and up-to-date understanding of cyber-physical systems in manufacturing settings. Similarly, Camara Dit Pinto *et al.* [32] investigate how DTs improve SA in the complex oil-and-gas industry. On the other hand, a deep understanding of SA is essential for developing IT systems that genuinely enhance it [36]. SA models focus on users' cognitive processes, linking them to systems that interpret situational information [85,86].

Incorporating SA considerations enables a shift from technology-centric designs to human-centered approaches [67,87] ensuring information aligns with users' mental models rather than merely presenting raw data. Building on this, Camara Dit Pinto *et al.* [32] explore how different DT components affect the three levels of SA, emphasizing that the user interface impacts all levels simultaneously. Later, they propose a methodology for designing DTs to enhance SA, introducing the concept of *reality anchors* [88]. These reality anchors – alarms, sensor data, process information, and environmental conditions – help users perceive, comprehend, and project system states, facilitating more informed decision-making. Fulfilling these SA requirements provides a structured approach to designing DT solutions with advanced computational capabilities that align with managerial cognitive processes and operational demands. This helps prevent information overload, mistrust and out-of-the-loop situations that lead to significant human errors [87].

2.6. Research gap

Despite growing attention to SA in construction management, there remains a lack of clarity on the relationship between specific SA requirements, the situation assessment process and the features of DTs impacting construction managers' cognition. On the one hand, practical studies on DTs increasingly reference SA [15,17,34], likely aligned with managers' intuitive interest in clearly understanding their system [89]. Yet, these studies often fail to specify which SA requirements their systems address and to what extent. Moreover, due to their technology-first approach, these studies provide limited insights into how DT solutions align with the cognitive processes involved in gaining and maintaining SA. Their analyses seldom clarify what technological features directly strengthen (or potentially undermine) managers' ability to accurately perceive, comprehend, and project potential disruptions. On the other hand, theoretical studies focusing on SA requirements have significantly enhanced our understanding of how construction managers perceive and process information [27,35]. However, these studies tend to overlook how construction managers maintain SA considering the influence of uncertain, high-pressure conditions and various work environments in the construction supply chain. Additionally, these studies do not yet offer concrete guidance on how existing or emerging DT features – such as interactive dashboards or predictive analytics – should be structured to align with the nuanced SA requirements in varying work environments. Given the acknowledged importance of SA, aligning DT developments with its principles is imperative for developing advanced solutions that effectively meet the challenges of human decision-makers in construction contexts.

3. Research design

This study employs a qualitative research design to define the SA requirements and the factors dynamically influencing SA, with the ultimate goal of formulating design guidelines for DTs in construction. The primary data collection method consisted of semi-structured interviews with senior management professionals, complemented by on-site, non-participant observations. Interviews have been widely recognized for their capacity to elicit knowledge from experienced practitioners [90] and generate nuanced insights into the SA requirements of managing personnel [29,70]. Unlike survey-based methods, interviews encourage open-ended dialogue and enable the interviewer to explore emergent themes in real time. Prior studies have underscored the effectiveness of such interviews in identifying and confirming information needs for both offsite [91] and on-site construction activities [31].

To complement the interviews and enhance data richness, subsequent non-participant observations of precast production and assembly processes were conducted. These observations took place after the in-person interviews with managers were completed at three precast element factories and two construction sites where precast elements were assembled. The aim was to gather implicit insights into information usage, focusing on detecting and assessing disruptions as they occurred. Unobtrusive observations serve as a reality-confirming supplement to interviews [92], analyzing events in real-time rather than as managers might ideally perceive them. Besides, researchers can observe which workflows are best optimized through information system support [93]. The observations conducted in this study enriched the findings from the interviews by making the relationship between the working environment of the managers and their SA dynamics more transparent.

3.1. Research setting and participant selection

We selected two representative settings within the lifecycle of a construction project – offsite production and on-site assembly of precast elements – to capture a broad view of SA requirements and disruption management. Offsite construction has emerged as a transformative approach for improving project timelines, resource utilization, and quality [94,95]. Frequent updates to production schedules, transportation constraints, and site readiness collectively generate an environment prone to unanticipated disruptions [65]. Consequently, the SA model offers a systematic lens and a valuable area of research for understanding and supporting the real-time cognitive demands typical of these dynamically evolving construction environments [71,81]. Identified SA requirements for detecting and assessing disruptions are valuable input for designing DTs with advanced computational capabilities that promise to enable construction managers to do their work effectively.

Participant selection followed a purposive expert sampling strategy, augmented by snowball referrals to reach additional professionals with specialized knowledge. Purposive sampling is a non-probability sampling technique that allows for the targeted recruitment of individuals directly involved in offsite production, on-site assembly, or developing IT solutions for prefabrication factories [96]. Initial contacts were identified via professional networks and publicly available information. Subsequently, the cohort was expanded through snowball sampling [97]. To ensure a high level of practical relevance, the study deliberately focused on experienced professionals with substantial involvement in infrastructure and residential construction projects. These senior managers offered insights grounded in long-term industry engagement. On the technology side, the selection targeted IT specialists from firms recognized for developing advanced digital solutions. This allowed the study to reflect current industry-leading practices in construction-related IT systems. This method facilitated the inclusion of individuals with niche expertise and ensured a robust representation of insights across multiple roles. In total, 13 experts were interviewed, with an average industry experience of 18.5 years (see Table 1). This sample size aligns with previous studies employing a GDTA framework, demonstrating the potential to generate actionable findings that inform academic and industry-led research [31]. Furthermore, it is consistent with cohort sizes used in prior research that successfully elicited expert knowledge to support the development of data models in construction-related contexts [98,99].

3.2. Data collection

Two interview rounds, with 16 interviews in total, were conducted to explore the cognitive processes during disruption management in the two different contexts (see Fig. 2.). Round 1 focused on discovering how offsite production and onsite assembly managers cognitively tackle unexpected events. These findings laid the groundwork for round 2, focused on refining and enhancing the insights. Such an iterative design aligns with recommended protocols for deriving comprehensive SA requirements, thereby strengthening the quality of results [87].

In round 1, 11 interviews were conducted using open-ended questions guided by the protocol outlined by Jiménez and Orozco [100]. Prompts aimed to uncover participants' everyday operational tasks and to evaluate how effectively existing IT systems – already containing critical operational data – support or fail to support their disruption management. The objective was also to uncover unmet information needs, prompting participants to discuss desired features or functionalities that have not yet been integrated into their IT systems.

Round 2 comprised five interviews, with three returning participants and two new subject-matter experts. In these sessions, we introduced the SA model (Fig. 1), demonstrating how it can frame disruption analysis in construction projects. An initial 15-minute briefing explained the principal elements of the SA model, illustrating its importance for real-time

Table 1
Overview of interviewees participating in the study (n = 13).

ID	Job Role	Focus Area	Experience [Years]	Interview type	Interview Duration [min]	
					Round 1	Round 2
1	Production Manager	Offsite Production	40	In-person	120	90
2	Production Manager	Offsite Production	24	In-person + Video call	75	–
3	Production Manager	Offsite Production	6	In-person	45	–
4	Project Leader	Offsite Production	7	Video call	60	–
5	Site Manager	Onsite Assembly	40	In-person	60	60
6	Site Manager	Onsite Assembly	21	In-person	–	90
7	Project Manager	Onsite Assembly	32	Video call	–	80
8	Information Manager	Offsite Production	11	Video call	60	–
9	Managing Director	IT Systems for Offsite Production Management	20	Video call	60	–
10	Software Developer	IT Systems for Offsite Production Management	6	In-person	130	60
11	Founder, CEO	IT Systems for Offsite Production Management	6	Video call	60	–
12	Product Manager, Planner	Offsite Production	16	Video call	60	–
13	Environmental Engineer	Offsite Production, Material Flows	12	In-person	60	–
			Ø = 18,5		∑ = 790	∑ = 380

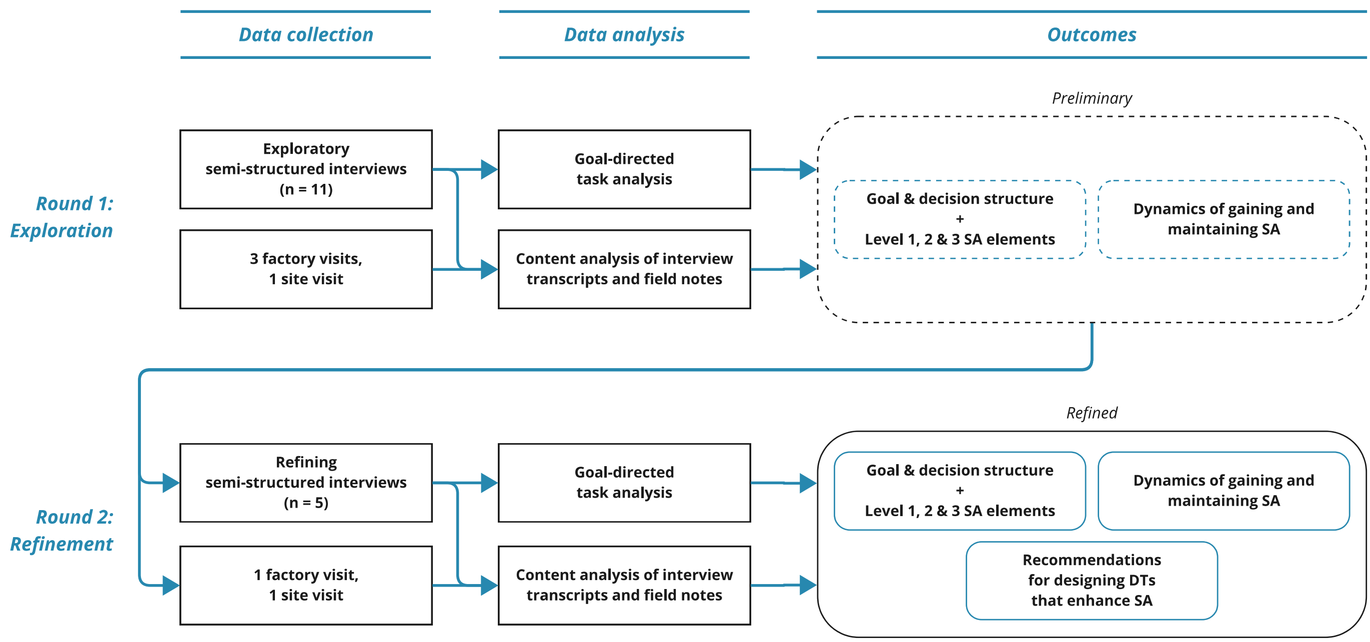

Fig. 2. Research design.

disruption resolution. We used a concise set of slides presenting a preliminary goal-decision architecture, followed by structured prompts such as, '*Are there other data points that might enhance your assessment of this issue?*' and '*How do you see this information shaping the next steps?*'. This format encouraged constructive input regarding the conceptual soundness and practical relevancy of SA requirements.

3.3. Data analysis

Once round 1 concluded, we employed a Goal-directed task analysis (GDTA) to translate the wide-ranging interview data into a preliminary structure of goals, decisions, and associated SA needs. GDTA systematically identifies the cognitive processes that human operators undertake and the vital information necessary to achieve their objectives, even when confronted with unfamiliar or unexpected situations [33]. Specifically, it examines the primary goals of operators, the critical decisions needed to fulfill these goals, and the SA requirements across three levels: perception, comprehension, and projection [87] (see Fig. 3). Widely recognized as a reliable approach, GDTA is frequently applied to explore SA in dynamic decision-making scenarios [101].

A key strength of GDTA is its focus on determining the ideal information operators should access to meet their goals, regardless of current technological limitations. This makes GDTA a technology-agnostic approach for formalizing experts' background knowledge, ensuring its relevance across different platforms in the fast-evolving construction DT field [44.108,103]. GDTA can serve as an evaluation criterion for automation, as Parasuraman, Sheridan and Wickens [104] highlighted, ensuring that the developed system supports rather than undermines

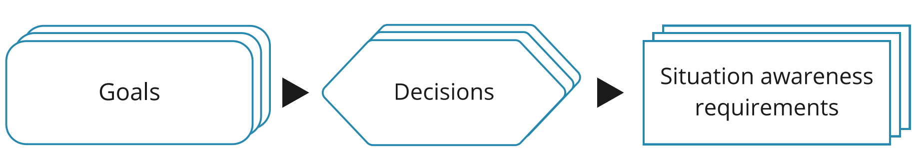

Fig. 3. The goal-directed task analysis establishes the relationshipbetween goals, decisions and SA requirements during dynamic decision-making.

human performance. Furthermore, GDTA has effectively facilitated communication between system designers and end-users by improving their understanding of specific scenarios, such as managing disruptions [105].

During the GDTA, the recorded interview data was systematically coded to form a comprehensive hierarchy, which included top-level goals, subgoals, and pivotal decisions. For each decision node, we identified SA requirements that span perception, comprehension, and projection. Table 2 shows examples of interviewee quotes related to information from each of these three levels. These examples explain how the SA levels apply to real-world situations. For instance, quotes at the perception level focus on immediate status information about a planned prefabricated element delivery, while those at the comprehension level explain the meaning of data, e.g., they are information important for identifying disruption. Quotes at the projection level describe potential future conditions based on the current situation, such as the impact of changes in processing orders in the factory.

Refinements based on round 2 feedback led to reconfiguring goals and decisions. The original structure, which outlined specific goals and decisions for each disruption type, was perceived by experienced managers in the factory and on the site as overly rigid. Managers found the initial structure overly prescriptive, advocating for a more flexible method to represent different types of disruptions. This aligns with the observations of Endsley and Jones [33], who stress the importance of maintaining relevance in goals and decisions even under unfamiliar or unforeseen conditions. As a result, specific SA components were revised, omitted, or augmented, culminating in an updated set of goals, decisions, and SA requirements that better reflect the complexities of disruption management.

To add depth to the GDTA results, we performed a comprehensive content analysis of the interview narratives, noting recurrent themes, challenges, and user behaviors. By coding textual data for patterns, challenges, and distinctive behaviors, we derived more nuanced insights into how SA components interact in practice. The GDTA and content analysis findings informed the design of specific DT features tailored to the observed user demands. While GDTA clarified critical SA requirements, content analysis contextualized the cognitive processes within the construction context where managers operate, ensuring that the derived DT design recommendations are academically robust and practically viable.

Table 2
Definition of SA levels with examples from the interviews and derived SA requirements.

SA Level	Definition	Quote from interviews	SA requirement
1	Perception of information elements in the environment	"The customer calls the factory / the dispatcher and says: 'Is my element now ready?'"	- Perceive the status of upcoming deliveries
2	Comprehension of the present situation	"Here I can see, for example, this pallet occupied this station for 21 min, whereas the planned takt time was 10 min – that is twofold, that is bad."	- Analyze machine productivity
3	Projection of the future status	„For example, if I postpone this project, what happens? What happens if the project is blocked? What are the consequences?"	- Project potential consequences of a disruption

4. Findings

4.1. Situation awareness requirements

A high-level goal and decision structure was compiled, focusing on the goals *Investigate disruptions during offsite production* (see Fig. 4) and *Investigate disruptions during onsite assembly* (see Fig. 5). Specifically, this structure centers on two principal objectives in each phase: detecting and assessing disruptions in offsite production and onsite assembly. Each goal is further subdivided into immediate subgoals addressing the identification of potential disruptions and the evaluation of their severity. This framework aligns with managers' primary concerns – timely recognition of disruptive events and the rapid assessment of their impact. Maintaining a higher-level structure in the GDTA enables a clear comparison of SA requirements across the two construction contexts. At the same time, it ensures critical dynamics are captured. Although additional subdivisions were considered, they were ultimately deemed impractical for this study, as the existing decisions already capture the principal triggers for prompt situation assessment.

Managers develop distinct mental models in offsite production and onsite assembly, a divergence rooted in the contrasting types and breadths of information they must process. In the factory, SA requirements predominantly involve internal factors – such as production order, machine status, and storage space. To understand these factors, factory managers must compare and assess quantitative metrics (e.g., production targets, time allocation at workstations, degrees of task completion, or storage level). Their projections at this stage remain similarly inward-focused. In contrast, accurately understanding onsite disruptions requires a more significant dimensional variability in managers' mental models. They must perceive and interpret multidimensional and highly interdependent information, such as activity statuses, spatial arrangements, work sequences, and resource allocation. Furthermore, SA in the assembly phase depends on internal (e.g., short-term schedules, site layout) and external factors (e.g., incoming deliveries, weather conditions). These external factors affect SA at all levels, necessitating a broader scope of awareness.

The goal and decision structure indicates that higher-level SA requirements become nuanced once the need moves beyond initial disruption detection to assessing their severeness. When examining offsite production processes, we found that the fundamental SA elements at level 1 exhibit significant overlap between subgoal 1.1 (identifying a disruption) and subgoal 1.2 (evaluating the severeness of a disruption) (Fig. 4). These core data elements, which include production metrics, prefabricated element storage, and production schedule, serve as a baseline for maintaining operational awareness. Notably, higher SA levels display sharper distinctions, as comprehension and projection for a rush order require a more profound analysis of workloads and prioritization of concurrent orders. A comparable pattern emerges in onsite assembly (Fig. 5), where subgoal 2.2 (assessing weather-related disruptions) necessitates not only the assessment of the extent of the weather but also the capacity to correlate its potential impact on specific activities, crews and equipment.

4.2. Dynamics of gaining and maintaining situation awareness

The identified SA requirements represent an idealized state encompassing all potential information necessary for effective disruption investigation. However, these requirements are inherently dynamic and cannot be considered static or conclusively fulfilled. As operational conditions evolve, it becomes imperative for managers to maintain an adaptive approach, continually refreshing their awareness to address and investigate emerging disruptions promptly and effectively. This need for ongoing renewal became especially clear when comparing offsite production to on-site assembly. Observational data and interviews revealed that managers in these two construction contexts use distinct approaches to maintain SA, underscoring how their

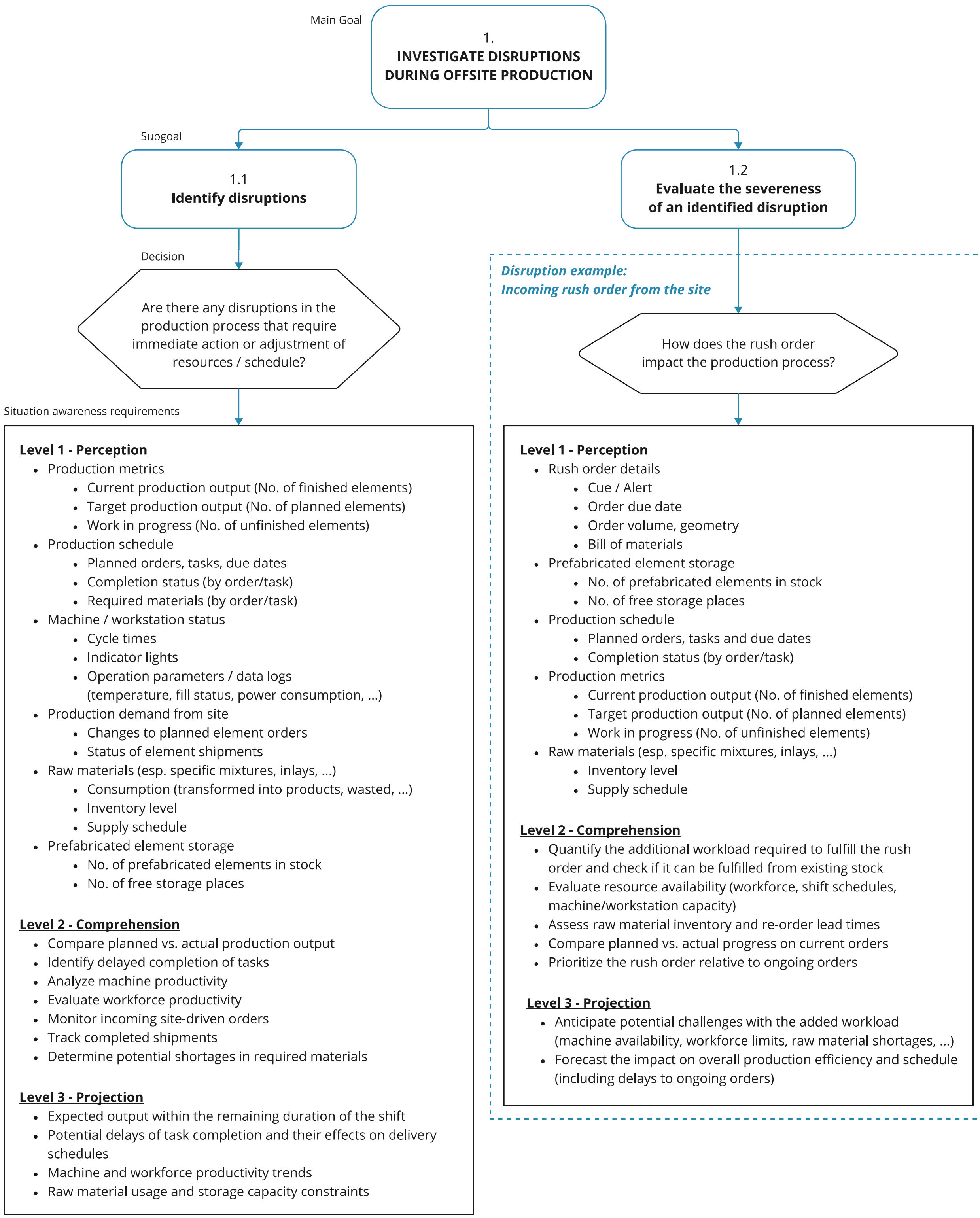

Fig. 4. Goal and decision structure with SA requirements for investigation of disruptions during offsite production.

surroundings, work principles and degrees of digitalization shape this process.

4.2.1. *Offsite production*

The approach to maintaining SA during offsite production is shaped by three interlinked factors: necessity to monitor overall performance while meeting high-stakes orders, the increasing role of digitally enhanced production monitoring, and structured work environments that enhance observational clarity.

Investigating potential disruptions often requires managers to maintain a broad overview of shift-based performance indicators while gaining an emergent, order-specific understanding of the situation. From our field observations, production managers primarily monitor aggregate metrics (SA level 1) – such as planned and actual outputs, machine cycle times, and real-time task durations – to gain immediate awareness of overall performance. These synthesized indicators enable

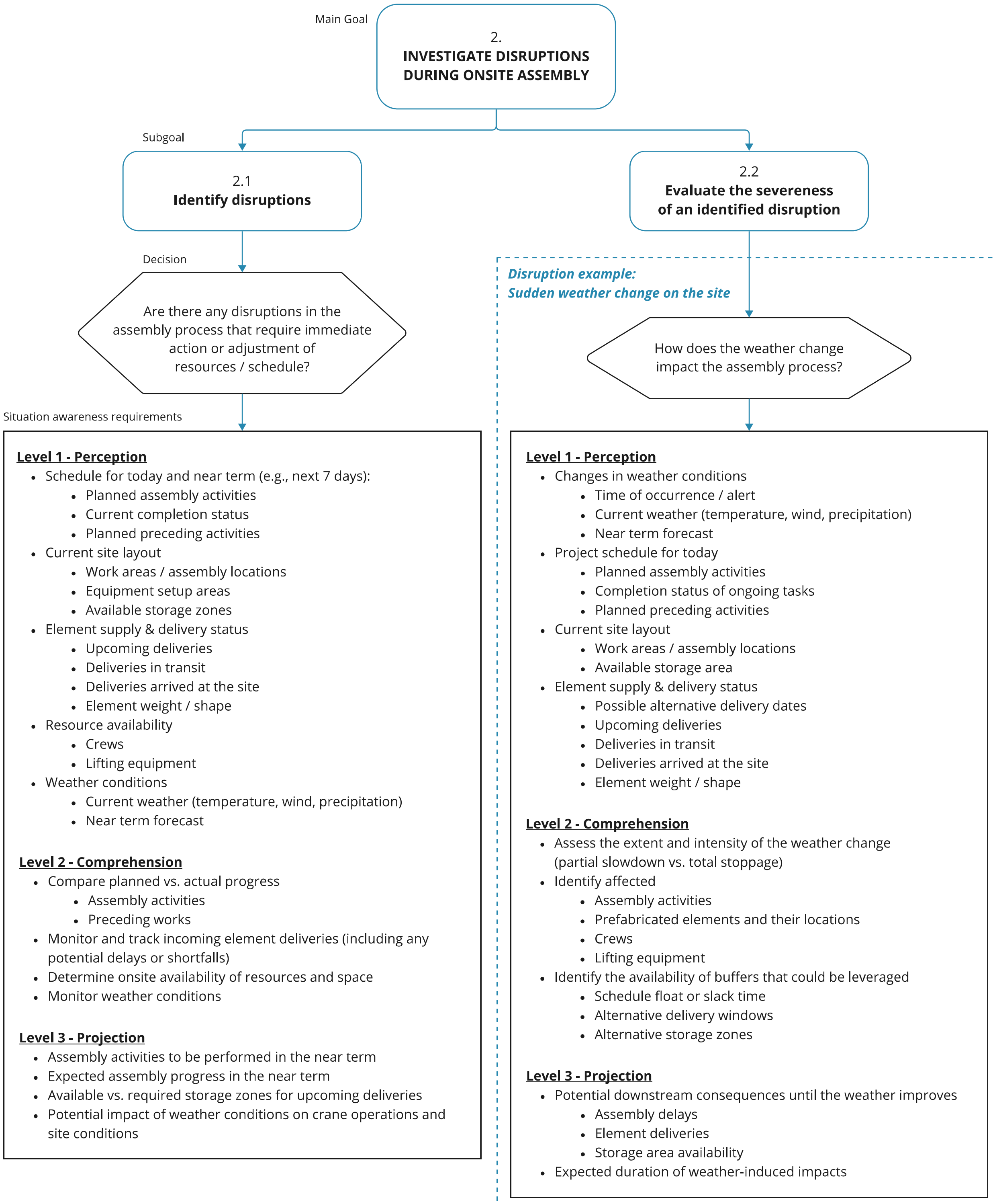

Fig. 5. Goal and decision structure with SA requirements for investigation of disruptions during onsite assembly.

them to comprehend ongoing trends and inefficiencies (SA level 2). However, when a rush order arrives or an existing high-stakes order begins to deviate from its planned schedule, managers must pivot from this macro-level disruption detection to an in-depth, order-specific focus. This refined perspective requires analyzing factors like current progress milestones, completion progress, and how prioritizing the urgent or high-stakes order may impact other orders in the pipeline. During this process, managers engage deeper comprehension (SA level 2) and projection (SA level 3) to anticipate potential downstream effects – such as delay of other deliveries or overtime requirements – and balance these risks against the strategic importance of the specific order. Thus, the ability to switch from macro-level disruption monitoring to micro-level investigation when critical orders arrive underlines the importance of adaptive managerial practices and robust SA throughout the production process.

In addition, these factories increasingly integrate digital tools to reinforce SA across all three levels. Real-time scoreboards positioned centrally on the shopfloor display planned versus actual progress, thereby triggering managers to decide when to zoom into specific issues. Machines with indicator lights that can be seen from a distance or positive/negative symbols on the dashboards provide operators and supervisors with instantaneous awareness of operational status (SA levels 1 and 2). Meanwhile, numeric trend indications project expected outputs based on current performance and existing disruptions, contributing partially to predictive capabilities (SA level 3). This synergy of physical consistency, repetitive workflows, and digital augmentation helps managers promptly identify disruptions.

The degree of task automation significantly influenced how managers developed and maintained SA. In the two facilities characterized by less automated processes, managers were required to closely oversee the initiation of production orders, ensure the timely execution of tasks, and coordinate the storage of finished elements within the warehouse. This hands-on approach necessitated a more advanced comprehension (SA level 2), as managers were often required to integrate fragmented work steps and analyze their temporal interdependencies to address disruptions effectively. In contrast, observations at the third facility, which operated a highly automated carousel production line integrated with an ERP/MES system, demonstrated a marked reduction in managerial engagement required for routine oversight. Automated systems within this environment generated real-time alerts for schedule deviations, initiated subsequent tasks autonomously and monitored task completion. Although the manager maintained a baseline understanding of task durations, the MES system's real-time, integrated data substantially reduced the cognitive effort required to gain SA for detecting emerging disruptions. These findings highlight how varying degrees of technological sophistication shape managerial involvement, with advanced digital systems streamlining – and partially automating – higher-level SA processes.

Lastly, interviews highlight how structured production layouts and fixed work zones support the initial and intermediate levels of SA. Centralized supervision and standardized workflows facilitate rapid perception (SA level 1), as managers can simultaneously observe several stations and promptly identify disruptions. Moreover, consistency in production processes and workload distribution aids comprehension (SA level 2) since stable metrics and benchmarks enable quick interpretation of performance data and deviations. One production manager, for example, emphasized how a balanced distribution of complicated and straightforward orders within a shift makes it easier to compare daily outputs across shifts and assess operational progress against established norms.

4.2.2. *Onsite assembly*

Maintaining SA during onsite assembly demands repeating cycles of data gathering, information interpretation and continuous re-evaluation. Managers must navigate shifting conditions, contextualize metrics against evolving site realities, and rely on their expertise to project future conditions.

In practice, managers gain SA in a heavily iterative manner: they perceive information items like assembly activities or weather forecasts (SA level 1), then evaluate how these might affect the assembly process (SA level 2) and return to check additional information such as the delivery status of precast elements (SA level 1). Deciding how often to re-check these level 1 items can depend on direct observations (e.g., visible changes in the work zone) and indirect cues (e.g., unusual delays in supply). During the interviews, managers describe this process as demanding because even minor changes – such as an unexpected delay in delivery – can force them to re-evaluate many of the other SA level 1 items. When managers notice signals of potential disruption, such as a sudden weather change (subgoal 2.1), they assess its seriousness and how it could impact other connected activities (subgoal 2.2). In doing so, they narrow their focus and gather the specific data most relevant to that issue. By looking more closely at one area, they try to gain deeper insight into how tasks and constraints fit together, uncovering interdependencies they might not have been aware of before.

Comprehension is frequently challenged by the fact that the meaning of metrics depends heavily on the specific context in which they are interpreted. Managers emphasized that metrics cannot be interpreted in isolation; each value must be compared against the scheduled plan and continuously re-evaluated as site conditions change. For instance, the daily count of assembled parts is not *good* or *bad,* absent a comparison with scheduled assembly benchmarks. This challenge becomes more pronounced because learning curves change workers' productivity and equipment performance over time. As one site manager explained, *"Not everything is static. So, the weather forecast is a static thing – it's either 5° or 4° or −1° or −3°. It's a statical figure. The production of people or the production of machinery on site is not statical. You always have a learning curve. Always, people learn onsite. So, the production you measure in one week could be different four weeks later. It's not the same. It is hardly ever the same."* Consequently, managers must account for these evolving conditions, adjusting their SA level 2 interpretation of productivity metrics to detect disruptions and maintain realistic assessments of project progress.

Based on site visits and interviews with project managers, we found that the rapidly shifting conditions of construction projects pose another ongoing challenge to maintaining SA. Because work zones, access points, and staging areas are continually reconfigured, installing stable visual aids – such as fixed lighting systems or centralized displays – proves impractical. Consequently, to maintain SA, site managers rely on systematic site monitoring, conducting regular visual inspections while moving around the work area to stay updated on evolving layouts and real-time site conditions. Alongside these inspections, managers engage in goal- and cue-driven conversations with on-site teams: they inquire about specific task progress (e.g., subgoal 2.1) or the impact of weather (subgoal 2.2). For example, just before the interview on the site, a foreman informed the manager about delayed steel girder installations – preceding works that needed to be completed for precast slab placement – this immediately alerted the site manager to a schedule disruption that might impact planned assembly activities. In addition, phone calls to offsite stakeholders, such as suppliers or colleagues, help managers gather cues from beyond the immediate work environment.

Given the difficulties in comprehension, projecting (SA level 3) whether a disruption will occur and evaluating its potential impact is found to be even more challenging. This process is heavily reliant on the experience and expertise of site managers. They report that they often perform these assessments intuitively without employing digital tools that could automate this procedure. For such projections to be accurate, experience plays an integral role. As one site manager noted, he routinely shares his knowledge with junior colleagues, warning them about what might happen if a particular situation occurs and instructing them on appropriate responses. This perspective underscores the importance of experience and long-term memory as individual factors for the development of SA to thoroughly examine assembly disruptions within the construction site environment.

4.3. *Digital twin design features to support situation awareness*

This section outlines design recommendations for DTs that enhance managerial SA in construction contexts (see Table 3 and Table 4). They are based on the previously identified SA requirements and the observed dynamics of gaining and maintaining SA. The recommendations are anchored in three core principles: *adaptability*, addressing evolving situations and disruptions; *contextual alignment*, maintaining relevance to work settings and dynamic construction scenarios; and *clarity*, ensuring essential information is readily discernible.

4.3.1. *Supporting situation awareness during offsite production*

To ensure adaptability to SA dynamics, DTs should enable effortless switching between macro-level views (e.g., entire production lines or factories) and micro-level analyses (e.g., individual projects or orders) for practical disruption assessment. To make this possible, the DT

Table 3
Key dynamics of gaining and maintaining SA during offsite production with recommended DT design features that enhance the SA of managers.

Dynamics of gaining and maintaining SA	Recommended DT design features to support SA
Macro-to-micro switching – Managers observe overall performance with aggregated metrics but pivot to order-specific details when urgent disruptions arise.	**Adaptive level of granularity in DT visualizations –** Provide interfaces that can swiftly toggle between broad factory views and focused views highlighting order-specific information.
Automation-driven adaptation of SA strategies – Managers adjust oversight strategies based on automation level, balancing manual checks or automated alerts.	**Context-specific DT processes based on automation levels –** Scale functionality to match automation needs, offering granular detail in manual settings and consolidated alerts in automated environments.
Synergistic integration of physical and digital cues – Managers leverage the synergy of physical structure (standardized layouts) and digital cues (indicator lights) for real-time assessments.	**Clear DT visualizations reflecting the physical environment –** Streamline data displays and shopfloor visualizations to highlight anomalies and trends with intuitive cues.

Table 4
Key dynamics of gaining and maintaining SA during onsite assembly with recommended DT design features that enhance the SA of managers.

Dynamics of gaining and maintaining SA	Recommended DT design features to support SA
Intensely iterative information processing – Managers follow iterative cycles: perceive site details (SA level 1), interpret implications (SA level 2), and then revisit SA level 1 items as new cues emerge.	**Adaptive display of relevant real-time data –** Integrate real-time data (e.g., deliveries, weather) with contextual factors (e.g., schedules, deliveries) in a dashboard, enabling rapid back-and-forth assessments.
Strong context-dependency of perceived values / metrics – Managers interpret metrics within ever-changing contexts (e.g., learning curves, weather), comparing them against shifting schedules.	**Ease contextual comparison of measured values –** Layer current performance metrics with historical records and ongoing plans, highlighting unexpected deviations or evolving benchmarks.
Projections require well-established mental models – Rely on experienced-based intuition to manually project potential disruptions (SA level 3) despite inherent challenges.	**Display likelihood and bandwidth of projections –** Offer projection tools that clearly display assumptions, outcome ranges, and confidence levels, letting managers question or refine these automated predictions.

interface could include an adaptive filtering system that highlights only the relevant metrics for a given project, thus reducing information overload. For example, when an order becomes time-sensitive or encounters potential delays, the plant manager will need to evaluate this specific order. The DT interface might automatically highlight key performance indicators such as material availability, current production rates, and scheduled tasks specific to that order. Meanwhile, production lines or resource pools unrelated to this order should be deprioritized for that moment into a minimal view, saving the manager's time and effort otherwise spent searching for relevant details. At the same time, to assess the impact on the broader workflow, the DT should keep the option to compare the specific order against other orders, helping managers anticipate downstream effects like schedule conflicts or resource shortages. By integrating these adaptive filters and dynamic correlation tools into the DT, managers can seamlessly move between monitoring general factory operations and assessing urgent orders.

Building on observations from diverse offsite production facilities, developers of DTs should aim to provide context-specific information that aligns with each environment's degree of technological sophistication and the respective distribution of managerial responsibilities. In less automated settings – where production management relies heavily on manual coordination – DTs should not only present relevant data to help managers perceive (SA level 1) the current status of tasks, resource usage, or machine states but also facilitate comprehension (SA level 2) by illustrating the interdependencies among these elements (e.g., how delays at one workstation might affect subsequent processes). Furthermore, when certain SA level 1 data is temporarily unavailable, DTs should explicitly provide cues about these interdependencies so that managers can infer the missing information from the available data. For instance, if direct data about a machine's status is absent, understanding how that machine typically interacts with downstream processes can help managers estimate its likely condition. This enhanced understanding positions managers to project (SA level 3) the potential impact on production schedules or internal resource requirements, thus enabling more proactive decision-making. Conversely, in more advanced environments – where enterprise systems automate much of the routine monitoring – DTs can support level 1 and 2 SA by aggregating and analyzing data in real-time, offering managers a consolidated view highlighting emerging issues. However, even in these high-tech contexts, managers must remain *in the loop,* periodically verifying the system's outputs and exercising critical oversight to ensure that automated processes do not obscure crucial details or undermine leadership roles. By aligning DT design with the distinct SA needs of differently automated environments, they can enhance responsiveness while preserving essential managerial involvement.

To ensure clarity, DT developments for offsite production should prioritize collecting valuable and relevant signals which prevents the excessive data flow described by one interviewee who recalled: *"In past roles, we've used different IoT sensors to capture real-time data and in – I'd have to look at the numbers again – but in the majority, most people that we would feed real-time data to, it was too, too much data to sift through based on the time that they have to synthesize or to sort of aggregate and synthesize that data"*. Algorithms can then parse these inputs for anomalies or trends, preventing decision-makers from manually sifting through raw data. Moreover, given the structured layout of work zones and defined work sequence in which work is executed, developers can favor streamlined, real-time 2D shopfloor representations focusing on the critical metrics (e.g., anomaly indicators, daily targets) over complex 3D factory views. As one interviewee describes: *"The operators on the shop floor, they can easily cope with the 2D view because they know 'I'm standing here'. […] It's just an overview of the whole hall, so that you can look over from your workstation. Then you see the machine has a fault. Is it in my work area? Okay, then I go to the machine briefly and check it."* Finally, these streamlined analytics can reinforce consistent benchmarking by providing clear progress indicators and day-to-day comparisons (e.g., workload distributions across shifts).

4.3.2. Supporting situation awareness during onsite assembly

DT should offer interfaces that adapt to managers' iterative cognitive processes. Investigating and assessing disruptions during onsite assembly requires a DT setup that continuously reflects the physical environment's fluctuations – from shifting work zones to dynamic weather conditions to changing delivery schedules. As elaborated in Section 4.2.2, managers cycle through SA level 1 (collecting site details) and SA level 2 (evaluating implications) and then re-evaluate level 1 as new cues appear. A DT should consolidate relevant data sources in one place, potentially via integrated dashboards. Rather than merely logging how many precast elements have been assembled or which truck deliveries have arrived, the platform should integrate these updates with related contextual factors – such as the current assembly schedule or weather-driven site constraints – to show managers what each new data point means for ongoing tasks. Tying each incoming information to specific goals (e.g., subgoal 2.1 around potential disruptions, subgoal 2.2 about their severeness) ensures managers can quickly navigate between the raw inputs and the *'so what?'* behind them.

Managers in our study emphasized that onsite performance metrics must always be judged against the specific context defined by scheduled targets and shifting benchmarks, given that productivity evolves in response to learning curves and other variables. Consequently, to support SA on the site, DT interfaces should do more than provide absolute numbers like *'X units installed'*. They should layer real-time data with a contextual comparison against both historical records and current plans. To prevent misinterpretation, the system could highlight whether the installation rate is unexpectedly low or high relative to historical records with similar conditions or whether the current day's output aligns with the planned milestone for that time. Making these reference points explicit helps managers detect disruptions sooner and refine their awareness about resource allocation or task sequencing. At the same time, it is crucial to recognize scenarios in which managers might question these automated assessments – especially if the presented data appears to conflict with their field observations. In such cases, the platform should provide avenues for reporting these doubts and systematically evaluating and adjusting the underlying comparison logic. Establishing a process whereby skepticism can be logged, examined, and reconciled fosters continuous refinement of the metrics and reinforces confidence in both the data and the analyses.

Finally, projecting the magnitude and likelihood of potential disruptions (SA level 3) is one of the most challenging steps for onsite managers, who often rely on their experience. To adapt to different degrees of experience, DTs could incorporate evaluations and bandwidth displays, showing not just a single output projection (e.g. '*forecasting an assembly of 50 elements by Friday*') but rather a range (*'forecasting an assembly of 40 to 60 elements by Friday, considering on the evident learning curve in the last days and stable weather forecast'*). Such transparent statistical process control charts can indicate how quickly a disruption might escalate if certain thresholds are reached given current and evolving conditions – enabling more proactive responses. Critical to this approach is transparency: whenever automated calculations or AI-driven models predict future outcomes, the system should openly indicate confidence levels or data certainty i.e., how those predictions were derived, how current or uncertain the inputs are, and what assumptions underpin them. As with the managers' intuitive judgments, these predictive features should remain straightforward to inspect and adjust, ensuring that even junior managers with less sophisticated mental models can fully understand and assess the trustworthiness of these results.

5. Discussion

This research provides novel insights into the SA requirements of construction managers addressing disruptions in two complementary contexts – offsite production and onsite assembly (RQ 1, Section 4.1). It focused on these two contexts because disruption management in construction often requires urgent, adaptive responses to ill-defined problems under intense time pressures [71]. Our findings indicate that disruption identification in offsite production relies predominantly on consistent, quantitative indicators since the production context remains uniform. In contrast, onsite assembly presents a more diverse work environment where SA requires processing multiple data streams – from detailed project schedules, subcontractor updates, and logistical details from offsite factories to external factors such as weather conditions. This need to acquire diverse, accurate, real-time information is a consistent challenge in disruption management [66]. Our results contribute to the suggestion by Kärkkäinen *et al.* [79] for a nuanced understanding of supply chain needs, showing how contrasting SA in offsite and onsite contexts highlights the role of tailored information flows in addressing disruptions. Furthermore, the study addresses the gap identified by Lappalainen *et al.* [27], who urge deeper investigations into SA demands among site personnel.

Additionally, this study examined how different work environments representing task / system factors in the SA model (see Fig. 1) influence how managers gain and maintain SA under disruptions (RQ 2, Section 4.2). The distinct cognitive strategies in offsite production and onsite assembly offer insights into managerial mental models. In offsite production, managers must swiftly shift between macro-level, overarching tasks – monitoring assembly-line capacity or tracking overall production timelines – and micro-level details focused on specific orders. This ability to move fluidly between overarching production workflows and detailed management of selected orders may indicate a high degree of managerial expertise. In onsite assembly, we observed iteration between various levels of SA as a critical pattern, likely due to the interdependency of activities, equipment, and prefabricated elements. It aligns with previous studies indicating that operators often re-evaluate perceived elements in light of their ongoing comprehension (SA level 2) and forward projections (SA level 3) rather than moving linearly from SA level 1 to level 3 [62,73]. Recognizing these iterative cognitive demands allows to embed more sophisticated knowledge-based reasoning techniques into DT systems, ensuring system recommendations align with managers' evolving mental models.

Our findings support the Endsley model for SA [36] about the influence of automation as a system factor (see Fig. 1) on human operators perceive and comprehend emerging situations. In highly automated factory environments, technology has shown to be capable of conducting preliminary perception tasks (SA level 1) and offers structured guidance for comprehension (SA level 2). This reduces managers' cognitive load. Such findings extend to Agrawal *et al.* [52], who propose various role distributions between human agents and DTs and argue for the importance of context-specific interfaces that promote effective human-DT interaction. Building on their work, our results emphasize that developments of sophisticated computational methods and higher degrees of automation provided by DTs should not exclude human insight; managers still must interpret nuanced information provided by the DT that might otherwise go unnoticed by technology alone. Furthermore, the challenge of achieving higher levels of SA – particularly level 3 – was apparent, especially during onsite assembly. It was found that managers often rely on tacit knowledge and expertise for projection. This illustrates the relevance of individual factors on SA as depicted in Endsley's model (see Fig. 1). These observations align with Lappalainen *et al.* [81] regarding the limited availability of higher-order SA systems in construction. Integrating AI-based predictive models with human judgment could help fill this gap. Still, such solutions demand rigorous validation to ensure that projections align with real-world disruptions and do not introduce new uncertainties [106].

Another contribution of this study is its articulation of how human-centered DT can be designed to align with the distinct cognitive processes of managers across diverse construction contexts (RQ 3, Section 4.3). During offsite production, factory managers should be able to easily filter and aggregate information for a specific project or high-stakes order, focusing attention on dynamic progress milestones, resource availability, and anticipated bottlenecks. This emphasis on selective information dissemination is a practical safeguard against information overload, sharpening the focus on relevant variables. To effectively support these cognitive processes in offsite production, visualization technologies such as interactive dashboards are a valuable area of research. They allow richer data access through drill-down capabilities and context-specific data filtering [107,108]. Aligned with this, backend features like complex event processing engines for digitally enhanced visual management [30,109] are up-and-coming candidates for further investigation. Meanwhile, the diversity of SA requirements in onsite assembly necessitates advanced data aggregation and real-time monitoring tools that gather information and prioritize it based on situational urgency. Future DTs for onsite processes may benefit from semantic-web pipelines that maintain machine-readable links across heterogeneous sources [10,12,44,116] and highly interactive, large-format dashboards [17]. Moreover, the present study emphasizes the importance of reflecting confidence levels or data certainty in these visualizations, especially in light of the growing adoption of AI-based data analyses [13,44,58]. Adopting microservice-oriented architectures may provide the flexibility to tailor DT capabilities to specific projects and user needs [6].

It is essential to recognize that while these technological propositions are based on observed SA needs in practice, they require careful contextual evaluation of their impact on SA in practical settings. As Endsley notes, “Each design should be empirically tested to identify any unforeseen issues that can negatively impact operator SA, and to allow the relative benefits of different design options to be considered.” [87] Adapting DT solutions to meet SA requirements in construction poses several challenges. Technically, many sites lack automated data-capture systems, limiting the availability of reliable SA level 1 information. Furthermore, organizational factors such as stakeholder reluctance to share critical data streams can undermine the effective implementation of DT-driven SA. One potential strategy to address this is using laboratory DT testbeds, providing controlled settings to experiment with and refine DT artifacts early on, thereby minimizing the risks of large-scale failures [87]. Though these testbeds can support the verification of DT concepts and mitigate implementation risks, they cannot fully replicate the nuances of naturalistic decision-making in actual construction practice.

The findings extend recent studies elaborating primarily on technical DT requirements and functionalities [3,7,9,112] by drawing attention to the context-sensitive nature of managerial cognition in day-to-day work. Integrating the observations of this study – derived through social science methods – into engineering informatics literature can significantly enhance the practical utility of future DT developments. A bottom-up approach that actively engages practitioners and analyzes their sensemaking processes is essential for transparent knowledge formalization and representation, ensuring that informatics solutions align with real-world needs [90]. Additionally, using the technology-agnostic perspective of GDTA ensures that the identified SA requirements remain relevant as DTs continue to evolve and gain traction in the construction sector.

A relevant takeaway is the conceptual distinction between SA processes and subsequent decision-making during disruption management. Evaluating these constructs independently allows researchers to investigate whether certain DT technologies excel in problem identification and sensemaking yet lack robust decision-support algorithms or vice versa. Endsley’s model also provides an intuitive language that enables practitioners to articulate their sensemaking with greater specificity, which supports more precise differentiation between understanding a situation and deciding how to act on it. Treating SA and decision-making as interdependent but distinct processes makes it possible to align DTs more effectively to improve human performance in factory-based and onsite construction settings. For instance, future work could integrate knowledge-based expert systems to support decisions once high SA is achieved, ensuring that real-time data streams and cognitive processes feed directly into automated or semi-automated reasoning modules.

This research has certain limitations that may influence the interpretation of its outcomes. One of these is its qualitative scope and the specific sample of interviewees, whose extensive insights may not represent the full spectrum of SA requirements or DT design recommendations. Although we minimized bias by selecting professionals with long expertise and diverse project backgrounds, the possibility remains that variations in factory settings or worker characteristics could influence the observed requirements. Nevertheless, our methods align with recognized qualitative approaches for SA investigation and knowledge elicitation in construction [70,98,99]. In addition, we adopted a deliberately high-level goal and decision structure to facilitate comparisons between offsite production and onsite assembly, which inevitably restricted the depth of our analysis for specific managerial activities. Additionally, training, stress, and organizational culture [35] can influence outcomes, even when SA is comprehensive.

This study focused on individual-centric scenarios where responsibility for disruption management rests with a single manager in the factory or on the site. While this helped isolate specific cognitive demands, many real-world construction projects involve distributed responsibilities (e.g., multi-expert project groups or, in the future, human-robot teams). Ensuring a common understanding of the information system will remain essential for the robust design and management of multi-domain DTs in complex, large-scale construction projects [77,113]. Moreover, shared SA becomes a critical factor in these contexts, as it more effectively reflects the psychological dynamics between individual experts shaping their collaborative problem-solving processes [62]. We recommend considering collaborative SA concepts, including distributed cognition, as additional lenses for analyzing these socio-technical systems [114,115]. Data collection methods like focus group interviews [116] or charrettes [117] could support this line of inquiry. Still, applying them in construction may require adjustments, as it can be challenging to gather practitioners with similar roles and a willingness to discuss their work routines openly in a joint event. Lastly, future investigations might employ mixed-methods approaches, adding quantitative performance metrics or simulation experiments to verify how different technological interventions influence SA and decision-making in real or near-real construction scenarios.

6. Conclusion

This study explored the intersection of SA and DTs in construction management, focusing on disruption management during offsite production and onsite assembly. Drawing on qualitative insights from 16 interviews and observations, the research applies GDTA and content analysis to identify specific SA requirements across these contexts, highlighting distinct cognitive processes managers employ to detect and assess disruptions. Key cognitive processes include shifting SA from macro-level production to micro-level order-specific SA during offsite production and demanding, iterative cycling across SA levels during onsite assembly. The results also reveal how automation and context-dependent challenges influence SA. These findings inform actionable recommendations for DT design – emphasizing adaptive, contextualized and transparent data visualization and projections – and advance our theoretical understanding of how knowledge representation and reasoning can be integrated into digital tools. The study contributes to a broader shift toward human-centric digital transformation in the construction industry by centering human cognition.

Future research could extend these findings through rigorous quantitative investigations measuring the direct impact of DTs on SA and the proposed DT design scheme in real-world construction projects. Extended case studies with deeper subdivisions within the GDTA could provide valuable insights, especially when the GDTA serves as a guiding framework for DT development to meet SA requirements. Practical case studies would also support an incremental and realistic implementation of DT systems. Additionally, exploring AI-driven decision-support systems that leverage SA insights is crucial, offering concrete examples of how human–machine collaboration enhances situational response. Examining SA from a team perspective – focusing on collaboration, role clarity, and information sharing – will also be essential for addressing dynamic team configurations and complex task demands. By integrating these dimensions, future research can help develop more comprehensive DT frameworks that align with the evolving needs of construction management and engineering informatics. Finally, advancements in real-time data capture, processing, and visualization technologies remain pivotal for fulfilling SA requirements and driving the practical adoption of DTs.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT and Grammarly in order to proofread and improve the readability and language of the manuscript. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Irfan Čustović: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation, Conceptualization. **Jianpeng Cao:** Writing – review & editing, Supervision, Conceptualization. **Daniel M. Hall:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Hans Wamelink:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to thank the interview partners for their valuable input and time. Their assessments and rich insights are greatly appreciated. We are also thankful for the feedback and comments from the anonymous reviewers that helped us improve upon the initial manuscript. This work is carried out within the project "Smart Mobile Factory for Infrastructure Projects (SMF4INFRA)" and supported by the Swiss National Science Foundation [grant no. 204852].

Data availability

The authors do not have permission to share data.

References

[1] M. Grieves, Intelligent digital twins and the development and management of complex systems, Digitaltwin 2 (2022), https://doi.org/10.12688/digitaltwin.17574.1.
[2] J. Whyte, L. Chen, C. Gamble, C. Genes, K. Pierce, J. Fitzgerald, D. Coca, M. Mayfield, F. Babovic, A. Pedro, N. Shah, Analysing systems interdependencies using a digital twin, Centre for Digital Built Britain, London, 2019.
[3] S. Kosse, V. Betker, P. Hagedorn, M. König, T. Schmidt, A semantic digital twin for the dynamic scheduling of industry 4.0-based production of precast concrete elements, Adv. Eng. Inf. 62 (2024) 102677, https://doi.org/10.1016/j.aei.2024.102677.
[4] Y. Yang, M. Li, C. Yu, R.Y. Zhong, Digital twin-enabled visibility and traceability for building materials in on-site fit-out construction, Autom. Constr. 166 (2024) 105640, https://doi.org/10.1016/j.autcon.2024.105640.
[5] Y. Jiang, M. Li, D. Guo, W. Wu, R.Y. Zhong, G.Q. Huang, Digital twin-enabled smart modular integrated construction system for on-site assembly, Comput. Ind. 136 (2022) 103594, https://doi.org/10.1016/j.compind.2021.103594.
[6] R. Chacón, H. Posada, C. Ramonell, M. Jungmann, T. Hartmann, R. Khan, R. Tomar, Digital twinning of building construction processes. Case study: a reinforced concrete cast-in structure, J. Build. Eng. 84 (2024) 108522, https://doi.org/10.1016/j.jobe.2024.108522.
[7] W. Long, Z. Bao, K. Chen, S.T. Ng, I.Y. Wuni, Developing an integrative framework for digital twin applications in the building construction industry: a systematic literature review, Adv. Eng. Inf. 59 (2024) 102346, https://doi.org/10.1016/j.aei.2023.102346.
[8] S. Su, R.Y. Zhong, Y. Jiang, J. Song, Y. Fu, H. Cao, Digital twin and its potential applications in construction industry: state-of-art review and a conceptual framework, Adv. Eng. Inf. 57 (2023) 102030, https://doi.org/10.1016/j.aei.2023.102030.
[9] C. Boje, S. Kubicki, A. Guerriero, Y. Rezgui, A. Zarli, Digital twins for the built environment, in: Buildings and Semantics, 1st ed., CRC Press, London, 2022, pp. 179–199, https://doi.org/10.1201/9781003204381-10.
[10] A. Borrmann, J. Schlenger, N. Bus, R. Sacks, AEC Digital Twin Data - why Structure matters, in: S. Skatulla, H. Beushausen (Eds.), Advances in Information Technology in Civil and Building Engineering, Springer International Publishing, Cham, 2023, pp. 651–669, https://doi.org/10.1007/978-3-031-35399-4_46.
[11] T. Li, Y. Rui, H. Zhu, L. Lu, X. Li, Comprehensive digital twin for infrastructure: a novel ontology and graph-based modelling paradigm, Adv. Eng. Inf. 62 (2024) 102747, https://doi.org/10.1016/j.aei.2024.102747.
[12] K. Farghaly, R. Soman, J. Whyte, cSite ontology for production control of construction sites, Autom. Constr. 158 (2024) 105224, https://doi.org/10.1016/j.autcon.2023.105224.
[13] A. Pal, J.J. Lin, S.-H. Hsieh, M. Golparvar-Fard, Automated vision-based construction progress monitoring in built environment through digital twin, Dev. Built Environ. 16 (2023) 100247, https://doi.org/10.1016/j.dibe.2023.100247.
[14] J. Schlenger, F. Pfitzner, A. Braun, S. Vilgertshofer, A. Borrmann, Digitaler Zwilling Baustelle – Baustellenüberwachung zur automatisierten Zeit- und Kostenkontrolle, Bautechnik 2023 (2023) 190–197, https://doi.org/10.1002/bate.202300005.
[15] R. Sacks, I. Brilakis, E. Pikas, H.S. Xie, M. Girolami, Construction with digital twin information systems, Data-Centric Engineering 1 (2020) e14.
[16] J. Zhang, J.C.P. Cheng, W. Chen, K. Chen, Digital twins for construction sites: concepts, LoD definition, and applications, J. Manag. Eng. 38 (2022) 04021094, https://doi.org/10.1061/(ASCE)ME.1943-5479.0000948.
[17] R.K. Soman, K. Farghaly, G. Mills, J. Whyte, Digital twin construction with a focus on human twin interfaces, Autom. Constr. 170 (2025) 105924, https://doi.org/10.1016/j.autcon.2024.105924.
[18] D. Liu, W. Lu, Y. Niu, Extended technology-acceptance model to make smart construction systems successful, J. Constr. Eng. Manag. 144 (2018) 04018035, https://doi.org/10.1061/(ASCE)CO.1943-7862.0001487.
[19] F. Vainionpää, M. Kinnula, A. Kinnula, K. Kuutti, S. Hosio, HCI and Digital Twins – A Critical Look: A Literature Review, in: Proceedings of the 25th International Academic Mindtrek Conference, ACM, Tampere Finland, 2022, pp. 75–88, https://doi.org/10.1145/3569219.3569376.
[20] C. Yang, H. Yu, Y. Zheng, L. Feng, R. Ala-Laurinaho, K. Tammi, A digital twin-driven industrial context-aware system: a case study of overhead crane operation, J. Manuf. Syst. 78 (2025) 394–409, https://doi.org/10.1016/j.jmsy.2024.12.006.
[21] A.A. Sezer, J. Bröchner, Site managers' ICT tools for monitoring resources in refurbishment, ECAM 27 (2019) 109–127, https://doi.org/10.1108/ECAM-02-2018-0074.
[22] X. Chen, A.Y. Chang-Richards, F.Y.Y. Ling, T.W. Yiu, A. Pelosi, N. Yang, Digital technology-enabled AEC project management: practical use cases, deployment patterns and emerging trends, ECAM (2024), https://doi.org/10.1108/ECAM-09-2023-0962.
[23] J.C. Bendul, M. Knollman, The human factor in production planning and control: considering human needs in computer aided decision-support systems, IJMTM 30 (2016) 346, https://doi.org/10.1504/IJMTM.2016.078921.
[24] P. Brauner, M. Ziefle, Why Consider the Human-in-the-Loop in Automated Cyber-Physical Production Systems? Two Cases from Cross-Company Cooperation, in: 2019 IEEE 17th International Conference on Industrial Informatics (INDIN), IEEE, Helsinki, Finland, 2019, pp. 861–866, https://doi.org/10.1109/INDIN41052.2019.8972142.
[25] T.B. Sheridan, R. Parasuraman, Human-automation interaction, Rev. Hum. Factors Ergon. 1 (2005), https://doi.org/10.1518/155723405783703082.
[26] M.R. Endsley, Designing for Situation Awareness in Complex System, in: Proceedings of the Second International Workshop on Symbiosis of Humans, Artifacts and Environment, Kyoto, Japan, 2001.
[27] E. Lappalainen, P. Uusitalo, O. Seppänen, A. Peltokorpi, A. Ainamo, A. Reinbold, User experiences of situational awareness systems in infrastructure construction, Constr. Manag. Econ. (2024) 1–14, https://doi.org/10.1080/01446193.2024.2366339.
[28] Y. Liu, W. Tong, Q. Li, F. Yao, Y. Li, H.X. Li, J. Huang, Study on complexity of precast concrete components and its influence on production efficiency, Adv. Civ. Eng. 2022 (2022) 9926547, https://doi.org/10.1155/2022/9926547.
[29] A. Sharma, S. Nazir, J. Ernstsen, Situation awareness information requirements for maritime navigation: a goal directed task analysis, Saf. Sci. 120 (2019) 745–752, https://doi.org/10.1016/j.ssci.2019.08.016.
[30] P. Eirinakis, G. Kasapidis, I. Mourtos, P. Repoussis, E. Zampou, Situation-aware manufacturing systems for capturing and handling disruptions, J. Manuf. Syst. 58 (2021) 365–383, https://doi.org/10.1016/j.jmsy.2020.12.014.
[31] E. Pillajo, C. Mourgues, V.A. González, Formalizing the information requirements for decision-making of field managers during indoor construction activities, ECAM (2023), https://doi.org/10.1108/ECAM-07-2022-0674.
[32] S.C.D. Pinto, E. Villeneuve, D. Masson, G. Boy, T. Baron, L. Urfels, Digital twin design requirements in downgraded situations management, IFAC-PapersOnLine 54 (2021) 869–873, https://doi.org/10.1016/j.ifacol.2021.08.102.
[33] M.R. Endsley, D.G. Jones, Situation awareness oriented design: review and future directions, Int. J. Hum.-Comput. Interaction 40 (2024) 1487–1504, https://doi.org/10.1080/10447318.2024.2318884.
[34] BIM2TWIN consortium, BIM2TWIN: Optimal Construction Management and Production Control (White paper), BIM2TWIN consortium, France, 2024.
[35] E. Pillajo, C. Mourgues, V.A. Gonzalez, Results of the goal-directed task analysis for formalizing the information requirements for decision-making of field managers during indoor construction activities. https://figshare.com/s/ebd033853f6cf8ac7d8d.
[36] M.R. Endsley, Design and Evaluation for Situation Awareness Enhancement, Proceedings of the Human Factors Society Annual Meeting 32 (1988) 97–101, https://doi.org/10.1177/154193128803200221.
[37] D. Jones, C. Snider, A. Nassehi, J. Yon, B. Hicks, Characterising the digital twin: a systematic literature review, CIRP J. Manuf. Sci. Technol. 29 (2020) 36–52, https://doi.org/10.1016/j.cirpj.2020.02.002.
[38] A. Bolton, M. Enzer, J. Schooling, The Gemini principles: guiding values for the national digital twin and information management framework, Centre Digital Built Britain Digital Framework Task Group (2018), https://doi.org/10.17863/CAM.32260.
[39] I. Čustović, R.K. Soman, P. Pauwels, D.M. Hall, Towards integrated digital twins for construction and manufacturing, in: Proceedings of the 2023 European Conference on Computing in Construction (EC3) and the 40th International CIB W78 Conference, European Council on Computing in Construction (EC3), Crete, Greece, 2023. https://doi.org/10.35490/EC3.2023.256.

[40] J.K. Liker, Toyota Way, Second Edition: 14 Management Principles from the World's Greatest Manufacturer, Second edition, McGraw Hill LLC, New York, N.Y., 2021.
[41] D. Guo, S. Mantravadi, The role of digital twins in lean supply chain management: review and research directions, Int. J. Prod. Res. 63 (2025) 1851–1872, https://doi.org/10.1080/00207543.2024.2372655.
[42] B. Barkokebas, M. Al-Hussein, F. Hamzeh, Assessment of digital twins to reassign multiskilled workers in offsite construction based on lean thinking, J. Constr. Eng. Manag. 149 (2023) 04022143, https://doi.org/10.1061/(ASCE)CO.1943-7862.0002420.
[43] A. Mayr, M. Weigelt, A. Kühl, S. Grimm, A. Erll, M. Potzel, J. Franke, Lean 4.0 - a conceptual conjunction of lean management and Industry 4.0, Procedia CIRP 72 (2018) 622–628, https://doi.org/10.1016/j.procir.2018.03.292.
[44] V.V. Tuhaise, J.H.M. Tah, F.H. Abanda, Technologies for digital twin applications in construction, Autom. Constr. 152 (2023) 104931, https://doi.org/10.1016/j.autcon.2023.104931.
[45] T. Weilkiens, Systems engineering with SysML/UML: modeling, analysis, design, Elsevier, 2011.
[46] C.A. Brown, Axiomatic Design for Products, Processes, and Systems, in: D.T. Matt, V. Modrák, H. Zsifkovits (Eds.), Industry 4.0 for SMEs, Springer International Publishing, Cham, 2020, pp. 383–401, https://doi.org/10.1007/978-3-030-25425-4_13.
[47] S. Kosse, P. Hagedorn, M. König, Analyzing modularity in construction digital twins for developing a dynamic modular reference architecture, In: ASCE International Conference on Computing in Civil Engineering (I3CE), Corvalis, USA, 2023.
[48] N. Bus, S. Oesau, F. Coudret, J. Schlenger, T. Yeung, M. Thorel, D2.1 – Digital Building Twin Requirements Analysis and Data Model, BIM2TWIN consortium, 2021.
[49] W. AlBalkhy, D. Karmaoui, L. Ducoulombier, Z. Lafhaj, T. Linner, Digital twins in the built environment: definition, applications, and challenges, Autom. Constr. 162 (2024) 105368, https://doi.org/10.1016/j.autcon.2024.105368.
[50] S. Aromaa, I. Lappalainen, E. Kaasinen, J. Öfversten, A Case Study—Applying a Design Thinking Process and User Experience Goals in developing Solutions for a Smart Construction Site, in: M.M. Soares, E. Rosenzweig, A. Marcus (Eds.), Design, User Experience, and Usability: Design Thinking and Practice in Contemporary and Emerging Technologies, Springer International Publishing, Cham, 2022, pp. 93–105, https://doi.org/10.1007/978-3-031-05906-3_8.
[51] J. Wilhelm, C. Petzoldt, T. Beinke, M. Freitag, Review of digital twin-based interaction in smart manufacturing: enabling cyber-physical systems for human-machine interaction, Int. J. Comput. Integr. Manuf. 34 (2021) 1031–1048, https://doi.org/10.1080/0951192X.2021.1963482.
[52] A. Agrawal, R. Thiel, P. Jain, V. Singh, M. Fischer, Digital twin: where do humans fit in? Autom. Constr. 148 (2023) 104749 https://doi.org/10.1016/j.autcon.2023.104749.
[53] M. Abdelmegid, A. Tezel, C.O. Sandoval, Z. Fang, W. Collinge, Conceptualizing Digital Twins in Construction Projects as Socio-Technical Systems, in: 41st International Symposium on Automation and Robotics in Construction (ISARC 2024), Lille, France, 2024. doi:10.22260/ISARC2024/0075.
[54] W. Kritzinger, M. Karner, G. Traar, J. Henjes, W. Sihn, Digital Twin in manufacturing: a categorical literature review and classification, IFAC-PapersOnLine 51 (2018) 1016–1022, https://doi.org/10.1016/j.ifacol.2018.08.474.
[55] M.T. Dzindolet, S.A. Peterson, R.A. Pomranky, L.G. Pierce, H.P. Beck, The role of trust in automation reliance, Int. J. Hum Comput Stud. 58 (2003) 697–718, https://doi.org/10.1016/S1071-5819(03)00038-7.
[56] T. Martin, J. Kivinen, J.E. Rijnsdorp, M.G. Rodd, W.B. Rouse, Appropriate Automation – Integrating Technical, Human, Organizational, Economic, and Cultural Factors, IFAC Proceedings 23 (1990) 1–19, https://doi.org/10.1016/S1474-6670(17)52057-1.
[57] R. Parasuraman, V. Riley, Humans and automation: use, misuse, disuse, abuse, Hum. Factors 39 (1997) 230–253, https://doi.org/10.1518/001872097778543886.
[58] F. Mostofi, O. Behzat Tokdemir, V. Toğan, A decision-support productive resource recommendation system for enhanced construction project management, Adv. Eng. Inf. 62 (2024) 102793, https://doi.org/10.1016/j.aei.2024.102793.
[59] J. Li, M. Shayboun, G. Calis, D. Calvetti, P. Demian, M. Kassem, M. Msawil, R. Soman, Toward a working theory for human-data interaction (HDI) in the built environment (BE), In: Proceedings of the 2024 European Conference on Computing in Construction (EC3), European Council on Computing in Construction (EC3), Crete, Greece, 2024 : p. 8. https://doi.org/10.35490/EC3.2024.282.
[60] M.A. Vidulich, P.S. Tsang, Mental Workload and Situation Awareness, in: G. Salvendy (Ed.), Handbook of Human Factors and Ergonomics, 1st ed., Wiley, 2012, pp. 243–273, https://doi.org/10.1002/9781118131350.ch8.
[61] M. Carmody-Bubb. Cognition and Decision Making in Complex Adaptive Systems: The Human Factor in Organizational Performance, Springer International Publishing, Cham, 2023, https://doi.org/10.1007/978-3-031-31929-7.
[62] M.R. Endsley, Situation awareness misconceptions and misunderstandings, J. Cognitive Eng. Decision Making 9 (2015) 4–32, https://doi.org/10.1177/1555343415572631.
[63] M.R. Endsley, Toward a theory of situation awareness in dynamic systems, Hum. Factors 37 (1995) 32–64.
[64] J.M. Schraagen, L.G. Militello, T. Ormerod, R. Lipshitz, Naturalistic decision making and macrocognition, Ashgate Publishing, United Kingdom, 2008.
[65] C.Z. Li, S. Wen, W. Yi, H. Wu, V.W.Y. Tam, Offsite construction supply chain challenges: an integrated overview, J. Constr. Eng. Manag. 150 (2024) 03124003, https://doi.org/10.1061/JCEMD4.COENG-14444.
[66] G. Yu, X. Qi, Introduction, in: Disruption Management: Framework, Models and applications, World Scientific, Singapore, 2004, pp. 1–30.
[67] X. Yuan, K.K.H. Ng, Q. Li, C.Y. Yiu, C.K. Lau, K.H. Fung, L.H. Ng, Exploring the human-centric interaction paradigm: augmented reality-assisted head-up display design for collaborative human-machine interface in cockpit, Adv. Eng. Inf. 62 (2024) 102656, https://doi.org/10.1016/j.aei.2024.102656.
[68] R. Prasanna, L. Yang, M. King, GDIA: a Cognitive Task Analysis Protocol to Capture the Information Requirements of Emergency First Responders, In: Proceedings of the 6th International ISCRAM Conference, Gothenburg, Sweden, 2009: p. 10.
[69] W.-C. Chang, A. Borowiak, S. Hasanzadeh, The importance of situational awareness in future construction work: toward the effects of faulty robots, trust, and time pressure, Comput. Civ. Eng. (2023) 821–828.
[70] J.G. Martinez, T. Yeung, R. Sacks, Y. Shahaf, L.-O. Sharoni, Situational awareness in construction using a serious game, J. Constr. Eng. Manag. 149 (2023) 04022183, https://doi.org/10.1061/JCEMD4.COENG-12521.
[71] L. Volker, Looking out to look in: inspiration from social sciences for construction management research, Construction Management and Economics 37 (2019) 13–23, https://doi.org/10.1080/01446193.2018.1473619.
[72] M.R. Endsley, From here to autonomy: lessons learned from human–automation research, Hum. Factors 59 (2017) 5–27, https://doi.org/10.1177/0018720816681350.
[73] J. Li, S. He, H. Lu, G. Xu, H. Wang, Modeling and risk assessment of workers' situation awareness in human-machine collaborative construction operations: a computational cognitive modeling and simulation approach, Adv. Eng. Inf. 63 (2025) 102951, https://doi.org/10.1016/j.aei.2024.102951.
[74] G. Klein, Sources of power: how people make decisions, 7th print, MIT Press, Cambridge Mass, 2001.
[75] G. Klein, J.K. Phillips, E.L. Rall, D.A. Peluso, A Data–Frame Theory of Sensemaking, in: Expertise out of Context, Psychology Press, 2007, pp. 118–160.
[76] K.E. Weick, Sensemaking in organizations, Sage Publications, Thousand Oaks, 1995.
[77] C. Rönndahl, P. Bosch-Sijtsema, R. Rempling, M. Karlsson, Making sense of collaboration in major infrastructure construction projects, Project Leader. Soc. 6 (2025) 100178, https://doi.org/10.1016/j.plas.2025.100178.
[78] B. Akinci, Situational awareness in construction and facility management, Front. Eng 1 (2014) 283, https://doi.org/10.15302/J-FEM-2014037.
[79] R. Kärkkäinen, R. Lavikka, O. Seppänen, A. Peltokorpi, Situation picture through construction information management, Emerald Reach Proc. Series (2019) 155–161, https://doi.org/10.1108/S2516-285320190000002028.
[80] R. Lavikka, P. Lahdenperä, M. Kiviniemi, A. Peltokorpi, Digital Situation Picture in Construction – Case of Prefabricated Structural Elements, in: E. Toledo Santos, S. Scheer (Eds.), Proceedings of the 18th International Conference on Computing in Civil and Building Engineering, Springer International Publishing, Cham, 2021, pp. 943–958, https://doi.org/10.1007/978-3-030-51295-8_65.
[81] E.M. Lappalainen, O. Seppänen, A. Peltokorpi, V. Singh, Transformation of construction project management toward situational awareness, ECAM 28 (2021) 2199–2221, https://doi.org/10.1108/ECAM-12-2020-1053.
[82] E. Lappalainen, P. Uusitalo, O. Seppänen, A. Peltokorpi, A. Reinbold, A. Ainamo, C. Görsch, R. Nyqvist, Situational management and digital situational awareness systems in infrastructure construction: managerial perspectives on relevance, challenges, and adoption, Buildings 14 (2024) 2035, https://doi.org/10.3390/buildings14072035.
[83] H.P.I. Halttula, O. Seppänen, Situational Awareness in Construction Projects Using Takt Production, in: Proc. 30th Annual Conference of the International Group for Lean Construction (IGLC), Edmonton, Canada, 2022: pp. 164–174. doi:10.24928/2022/0119.
[84] M. Eckhart, A. Ekelhart, E. Weippl, Enhancing Cyber Situational Awareness for Cyber-Physical Systems through Digital Twins, in: 2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), IEEE, Zaragoza, Spain, 2019, pp. 1222–1225, https://doi.org/10.1109/ETFA.2019.8869197.
[85] F.E. White, Data fusion lexicon, defense technical information center, Fort Belvoir VA (1991), https://doi.org/10.21236/ADA529661.
[86] A.N. Steinberg, C.L. Bowman, F.E. White, Revisions to the JDL Data Fusion Model, In: A1AA Missile Sciences Conference, Montery, USA, 1998: p. 17.
[87] M.R. Endsley, B. Bolté, D.G. Jones, Designing for situation awareness: an approach to user-centered design, Taylor & Francis, London ; New York, 2003.
[88] S. Camara Dit Pinto, É. Villeneuve, D. Masson, G.A. Boy, L. Urfels, Reality anchor methodology: how to design a digital twin to support situation awareness, J. Eng. Des. 35 (2024) 775–799, https://doi.org/10.1080/09544828.2024.2336838.
[89] D.G. Jones, A practical perspective on the utility of situation awareness, J. Cognitive Eng. Decision Making 9 (2015) 98–100, https://doi.org/10.1177/1555343414554804.
[90] T. Hartmann, A. Trappey, Advanced Engineering Informatics - philosophical and methodological foundations with examples from civil and construction engineering, Dev. Built Environ. 4 (2020) 100020, https://doi.org/10.1016/j.dibe.2020.100020.
[91] G. Lee, C.M. Eastman, R. Sacks, Twelve design patterns for integrating and normalizing product model schemas, Comput.-Aided Civ. Eng. 22 (2007) 163–181, https://doi.org/10.1111/j.1467-8667.2007.00475.x.
[92] G.E. Gorman, P. Clayton, Qualitative research for the information professional: a practical handbook, 2nd ed, facet publishing, London, 2005.

[93] T. Hartmann, M. Fischer, J. Haymaker, Implementing information systems with project teams using ethnographic–action research, Adv. Eng. Inf. 23 (2009) 57–67, https://doi.org/10.1016/j.aei.2008.06.006.
[94] W. Pan, R. Sidwell, Demystifying the cost barriers to offsite construction in the UK, Constr. Manag. Econ. 29 (2011) 1081–1099, https://doi.org/10.1080/01446193.2011.637938.
[95] F. Kedir, D.M. Hall, Resource efficiency in industrialized housing construction – a systematic review of current performance and future opportunities, J. Clean. Prod. 286 (2021) 125443, https://doi.org/10.1016/j.jclepro.2020.125443.
[96] G.K. Mweshi, K. Sakyi, Application of sampling methods for the research design, ABR 8 (2020) 180–193, https://doi.org/10.14738/abr.811.9042.
[97] M.J. Salganik, D.D. Heckathorn, 5. sampling and estimation in hidden populations using respondent-driven sampling, Sociol. Methodol. 34 (2004) 193–240, https://doi.org/10.1111/j.0081-1750.2004.00152.x.
[98] I. Fitkau, T. Hartmann, An ontology-based approach of automatic compliance checking for structural fire safety requirements, Adv. Eng. Inf. 59 (2024) 102314, https://doi.org/10.1016/j.aei.2023.102314.
[99] S. Rezaeifam, E. Ergen, H.M. Günaydın, Fire emergency response systems information requirements' data model for situational awareness of responders: a goal-directed task analysis, J. Build. Eng. 63 (2023) 105531, https://doi.org/10.1016/j.jobe.2022.105531.
[100] T.R. Jiménez, M. Orozco, Prompts, not questions: four techniques for crafting better interview protocols, Qual. Sociol. 44 (2021) 507–528, https://doi.org/10.1007/s11133-021-09483-2.
[101] A. Nasser-dine, A. Moise, J. Lapalme, Does explicit categorization taxonomy facilitate performing goal-directed task analysis? IEEE Trans. Human-Mach. Syst. 51 (2021) 177–187, https://doi.org/10.1109/THMS.2021.3066456.
[102] W. Saif, S. RazaviAlavi, M. Kassem, Construction digital twin: a taxonomy and analysis of the application-technology-data triad, Autom. Constr. 167 (2024) 105715, https://doi.org/10.1016/j.autcon.2024.105715.
[103] E. Hedayati, A. Zabihi Kolaei, M. Khanzadi, G. Ghodrati Amiri, Implementation of hardware technologies in offsite construction (2014–2023), in: Automation Construction, 170, 2025, https://doi.org/10.1016/j.autcon.2024.105948.
[104] R. Parasuraman, T.B. Sheridan, C.D. Wickens, A model for types and levels of human interaction with automation, IEEE Trans. Syst., Man, Cybern. A 30 (2000) 286–297, https://doi.org/10.1109/3468.844354.
[105] F.A. Mondragon Solis, J. Howe, W.J. O'Brien, Integration of information technologies into field managers' activities: a cognitive perspective, J. Manag. Eng. 31 (2015) A4014001, https://doi.org/10.1061/(ASCE)ME.1943-5479.0000302.
[106] M.R. Endsley, Humans and Machines Joining Forces, In: Collaborative Intelligence: How Humans and AI Are Transforming Our World, 1st ed., MIT Press, 2024: p. 61.
[107] B. Bach, E. Freeman, A. Abdul-Rahman, C. Turkay, S. Khan, Y. Fan, M. Chen, Dashboard design patterns, IEEE Trans. Visual Comput. Graphics (2022) 1–11, https://doi.org/10.1109/TVCG.2022.3209448.
[108] A. Sarikaya, M. Correll, L. Bartram, M. Tory, D. Fisher, What do we talk about when we talk about dashboards? IEEE Trans. Visual Comput. Graphics 25 (2019) 682–692, https://doi.org/10.1109/TVCG.2018.2864903.
[109] K. Murata, On the role of visual management in the era of digital innovation, Procedia Manuf. 39 (2019) 117–122, https://doi.org/10.1016/j.promfg.2020.01.246.
[110] J. Schlenger, K. Pluta, A. Mathew, T. Yeung, R. Sacks, A. Borrmann, Reference architecture and ontology framework for digital twin construction, Autom. Constr. 174 (2025) 106111, https://doi.org/10.1016/j.autcon.2025.106111.
[111] X. Shen, S.M.E. Sepasgozar, M.J. Ostwald, Knowledge-based semantic web technologies in the AEC sector, Autom. Constr. 167 (2024) 105686, https://doi.org/10.1016/j.autcon.2024.105686.
[112] S. Kosse, O. Vogt, M. Wolf, M. König, D. Gerhard, Requirements Management for Flow Production of Precast Concrete Modules, in: S. Skatulla, H. Beushausen (Eds.), Advances in Information Technology in Civil and Building Engineering, Springer International Publishing, Cham, 2024, pp. 687–701, https://doi.org/10.1007/978-3-031-35399-4_48.
[113] Y. Jiang, M. Li, W. Wu, X. Wu, X. Zhang, X. Huang, R.Y. Zhong, G.G.Q. Huang, Multi-domain ubiquitous digital twin model for information management of complex infrastructure systems, Adv. Eng. Inf. 56 (2023) 101951, https://doi.org/10.1016/j.aei.2023.101951.
[114] A.D. Landmark, E. Arica, B. Kløve, P.F. Kamsvåg, E.A. Seim, M. Oliveira, Situation Awareness for Effective Production Control, in: F. Ameri, K.E. Stecke, G. Von Cieminski, D. Kiritsis (Eds.), Advances in Production Management Systems. Production Management for the Factory of the Future, Springer International Publishing, Cham, 2019, pp. 690–698, https://doi.org/10.1007/978-3-030-30000-5_84.
[115] J.Z. Bakdash, L.R. Marusich, K.R. Cox, M.N. Geuss, E.G. Zaroukian, K.M. Morris, The validity of situation awareness for performance: a meta-analysis, Theor. Issues Ergon. Sci. 23 (2022) 221–244, https://doi.org/10.1080/1463922X.2021.1921310.
[116] S. Kim, J. Irizarry, R. Kanfer, Multilevel goal model for decision-making in UAS visual inspections in construction and infrastructure projects, J. Manag. Eng. 36 (2020) 04020036, https://doi.org/10.1061/(ASCE)ME.1943-5479.0000803.
[117] G.E. Gibson, D.A. Whittington, Charrettes as a method for engaging industry in best practices research, J. Constr. Eng. Manag. 136 (2010) 66–75, https://doi.org/10.1061/(ASCE)CO.1943-7862.0000079.