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DESIGNING REMOTE MONITORING FOR SMART MANUFACTURING FACILITIES: HAZARD IDENTIFICATION AND CLASSIFICATION

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ABSTRACT

This study investigates the process of hazard identification in complex manufacturing environments during the design phase, emphasizing the significance of the design process in developing designs that effectively mitigate hazards in contexts with numerous variables, such as a variety of machines, sensors, actuators, and agents. Through a mixed-methods approach, the objective of this work is to understand how the evolution of design outcomes across various stages might influence a designer's ability to recognize both standard and novel hazards. To achieve this understanding, an experimental design task was conducted with six designers from a national lab specializing in manufacturing technologies. This approach combined qualitative and quantitative data analysis from a one-hour virtual session with participants. Findings suggest that the complexity of identifying hazards in a high-dimensional design space is challenging within a limited time frame and that the identification of hazards is significantly influenced by the stage of the design task and the initial design decisions, indicating the need for extended time and strategic initial planning in the design process to enhance hazard identification.

Keywords: Advanced Manufacturing, Remote Monitoring Systems, Cyber-Physical Systems, Hazard Identification, Design Methods, Design Processes

1. INTRODUCTION

The manufacturing sector is undergoing a transformative shift towards more dynamic, interconnected ecosystems, primarily driven by the rapid advancements in Industry 4.0 and 5.0 technologies [1]. This primarily includes the integration of cyber-physical systems (CPS) and Internet of Things (IoT) technologies [2]. These technologies promise to enhance operational efficiency and adaptability, enabling manufacturers to respond more swiftly to market changes and customer demands, which in turn, is reshaping the traditional manufacturing landscape.

In an overview of the future of advanced manufacturing, Arinez et al. emphasize the adoption of strategies for adaptive planning, scheduling, and control mechanisms that are not only responsive but also predictive, capable of anticipating changes and adjusting in real-time [3]. This responsiveness can be directed at machines or the manufacturing environment itself. In the latter, a dynamic manufacturing factory is created, where the role of CPS and IoT cannot be overstated. These technologies provide the backbone for real-time data capture, analysis, and feedback, essential for adaptive planning and control.

Amidst these technological advancements, Operator 4.0 and Management 4.0 concepts have gained prominence, emphasizing the critical integration of human factors into the manufacturing equation. Operator 4.0 embodies the vision of empowering factory workers with digital tools and augmented capabilities, facilitating human-machine collaboration that enhances productivity and safety[4]. For example, Romero et al. developed a typology of eight main descriptors for the empowered operator of the future: augmented, virtual, healthy, analytical, collaborative, smarter, social, and super-strength [5]. Similarly oriented towards manufacturing efficiency, Management 4.0 focuses on leveraging smart technologies to improve process control, reduce human error, and enable rapid, data-driven decision-making [6]. Together, these approaches foster a manufacturing environment where human intelligence and creativity are augmented by digital capabilities, leading to improved system performance and worker satisfaction. However, the journey towards fully adaptive and human-centric manufacturing ecosystems is not without challenges. Manufacturers face issues related to demand variability, complex supply chain dynamics, and the need for rapid, accurate decision-making. Adaptive strategies that address the inherent complexities in the design of these future manufacturing environments are needed.

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2. BACKGROUND

2.1 Manufacturing Remote Monitoring Systems

Remote Monitoring Systems (RMS) have emerged as pivotal tools, transforming how factories operate and manage their resources. At the heart of RMS is the ability to provide real-time, continuous insights into various aspects of manufacturing operations, from production lines to machine tool status. This real-time data acquisition and analysis capability is not just about monitoring; it's about enabling a proactive approach to manufacturing management, where decisions are data-driven, and optimizations are made in real time to enhance efficiency and productivity. There are several ways, detailed below, in which the combination of RMS with technology such as IoT can transform manufacturing processes.

Production Lines. IoT has significantly propelled the capabilities of RMS forward, allowing for an unprecedented level of connectivity and data exchange across manufacturing systems. Huang, motivated by the demand for remote monitoring of production lines, develops an IoT platform focused on optimized data fusion and mitigating redundant sensor data [7]. IoT devices embedded within manufacturing equipment and production lines serve as RMS's sensory input, feeding a constant stream of operational data into the system. Theoretically, this integration facilitates a granular view of manufacturing processes, identifying bottlenecks, inefficiencies, and potential failures before they escalate into major issues.

Machine Tool Status. In terms of machine tool status monitoring, RMS equipped with IoT technology offers a real-time window into the operational health of critical manufacturing equipment [8]. This capability is crucial for maintaining the continuity of production processes, as it allows for the early detection of wear, tear, or malfunction in machine tools. One of the primary benefits is enabling predictive maintenance strategies, compared to to traditional reactive or scheduled maintenance approaches. By leveraging real-time data from RMS, manufacturers can predict equipment failures before they occur, facilitate greater operational transparency and control, and enable manufacturers to monitor production processes precisely. This not only prevents costly downtime but also extends the lifespan of manufacturing equipment, contributing to long-term operational sustainability. To highlight the business value of RMS and machine tool status, Momeni et al. studied six engineering firms to show that alongside the standard preventative maintenance benefits, customers benefit from ease of knowledge access and data validity when physical distance to machines would otherwise be a barrier [9].

Supply Chain. The adoption of RMS and IoT technologies also has profound implications for supply chain management within manufacturing. The real-time visibility and control afforded by RMS extend beyond the confines of individual manufacturing facilities, encompassing the entire supply chain. This enhanced visibility enables more effective coordination of supply chain activities, reducing lead times, and optimizing inventory levels. Moreover, the data-driven insights generated by RMS can inform strategic supply chain decisions, from supplier selection to logistics optimization, thereby improving overall supply chain resilience and responsiveness. Similarly, cloud platforms can facilitate the implementation of sophisticated RMS solutions that can adapt to evolving manufacturing needs through scalable, accessible, and secure data storage and analysis. This is shown by Hao et al., who sought to integrate cloud and IoT for OEMs (original equipment manufacturers) to have remote machine access and monitoring [10]. Cloud platforms also enable seamless integration of RMS data with other enterprise systems, such as Enterprise Resource Planning (ERP) and Supply Chain Management (SCM) systems, fostering a holistic approach to manufacturing management.

Service Value. Beyond the immediate operational benefits, the integration of RMS and IoT heralds a transformation in the service dimension of manufacturing, particularly through servitization [11]. Servitization refers to the evolution of manufacturing firms from purely product-centric to service-oriented business models, where value is increasingly derived from the provision of comprehensive service offerings alongside traditional products. RMS and IoT technologies are pivotal in enabling this shift, as they provide the necessary infrastructure for delivering advanced services such as remote diagnostics, usage-based pricing models, and performance-based contracts. This shift not only opens up new revenue streams but also aligns manufacturers more closely with the evolving needs and success factors of their clients.

2.2 Hazards in (Dynamic) Manufacturing Environments

Manufacturing environments, characterized by their fast-paced and interconnected nature, are fraught with a myriad of hazards that could compromise human operators' safety and the integrity of manufacturing processes and infrastructure. The advent of Industry 4.0 technologies, while heralding unprecedented efficiency and adaptability, also introduces new dimensions of risk created by dynamic or ambient intelligent manufacturing environments that must be meticulously managed. Efforts to mitigate the hazards found in ambient intelligent environments in the engineering design literature [12] are built upon in this work in the context of manufacturing environments. This section outlines the various categories of hazards inherent in such environments and underscores the criticality of robust hazard identification and risk management strategies.

At the forefront are **physical hazards**, which directly threaten the bodily safety and health of individuals involved in manufacturing operations. These hazards range from immediate dangers like machinery-related injuries to long-term health risks such as exposure to hazardous materials or ergonomic issues stemming from repetitive tasks [13]. **Environmental hazards** pertain to the impact of manufacturing activities on the natural environment, including pollution, resource depletion, and waste management challenges. Khezri et al. provide an example of design for environmental hazards, where they focus on reconfigurable manufacturing systems, which can be reconfigured based on evolving environmental needs [14].

The digitalization of manufacturing processes brings about **digital hazards**, primarily related to data integrity and cybersecurity. As manufacturing systems become increasingly reliant on data-driven decision-making and interconnected networks, the risk of data breaches, unauthorized access, and system disruptions escalates [15]. **Legal hazards** encompass the potential for litigation arising from non-compliance with industry regulations, safety standards, or intellectual property infringements. With their complex supply chains and international operations, dynamic manufacturing environments must navigate a labyrinth of legal requirements, making compliance an ongoing challenge. Prior research exists in understanding how manufacturing environments might comply with regulations within the country of production [16]. Additionally, prior work from Sharma et al. showed legal implications as one of several barriers to implementing the newest manufacturing technologies [17].

The social implications of manufacturing practices, particularly in terms of their impact on workplace relationships, community interactions, and social perceptions, constitute **social hazards**. Issues such as labor disputes, community backlash against environmental practices, or the social ramifications of automation and job displacement fall under this category. Addressing social hazards requires a commitment to ethical practices, community engagement, and transparent communication. Frameworks for socially responsible and ethical considerations in manufacturing have been forwarded in the literature [18, 19].

Lastly, **emotional hazards** refer to the psychological well-being of individuals within the manufacturing environment, encompassing stress, anxiety, and the potential for burnout. The high-stress nature of dynamic manufacturing operations, coupled with the demands of adaptability and continuous learning, can exert significant emotional strain on workers. Some studies have found correlations between burnout and exhaustion in manufacturing sectors due to more emotional human factors. Macias et al. found relationships between burnout and co-worker or supervisor support, while Zhou et al. studied burnout in female manufacturing workers in relation to factors like emotional exhaustion, over-commitment, job strain, and de-personalization [20, 21].

The complexity of dynamic manufacturing environments demands a holistic approach to hazard identification and risk management, encompassing a wide range of potential risks from physical to environmental. Developing comprehensive strategies that are anticipatory, adaptive, and inclusive of human factors is paramount to safeguarding both human operators and manufacturing processes, thereby ensuring the resilience and sustainability of manufacturing operations in the face of evolving challenges.

2.3 Research Gap

There are two main research gaps to be addressed in this study in relation to RMS and hazard identification. First, there is a need to address the efficacy of design processes for identifying hazards within manufacturing environments. The complexity and dynamism of modern manufacturing operations, characterized by the integration of cyber-physical systems and sophisticated production technologies, demand design processes capable of foreseeing and mitigating potential risks. However, questions linger regarding the current capability of design methodologies to systematically and effectively identify the spectrum of hazards that these new technologies introduce.

The second research gap lies in the integration of human factors within the design processes for RMS. As manufacturing systems become increasingly automated and reliant on RMS and cyber-physical systems, the role of the human operator evolves. This evolution necessitates design processes that not only account for technological and operational hazards but also prioritize the overall well-being, safety, and adaptability of human operators within these complex systems. The extent to which current design methodologies embed human factors into the development and implementation of manufacturing technologies remains unexplored.

In response to the identified research gaps, this study aims to enhance the knowledge base in manufacturing design, focusing on the development of cyber-physical systems that support RMS and are safe, efficient, and human-centered. The core question of this research explores how designers conceive of cyber-physical systems for RMS, particularly with an eye towards identifying and mitigating potential hazards. To conceive these systems, participants interact with an array of asset types: manufacturing equipment, sensors, actuators, processors, and operating agents. This investigation is structured around three specific research questions to understand participant interaction with these assets, and thereby shed light on design processes for cyber-physical manufacturing systems that support RMS.

RQ1: What does the distribution, variability and prioritization of asset types indicate about design strategies for remote manufacturing monitoring systems?

RQ2: How might the quantity and variety of assets used reflect on cognitive load and strategic design focus?

RQ3: How might the types and severity of hazards identified over time reflect the intuition and perception of manufacturing hazards and design responsibility?

The research questions will be addressed using data collected from a design procedure conducted with participants from a manufacturing demonstration facility (MDF). Manufacturing Demonstration Facilities (MDFs) play a critical role in fostering innovative design processes that are central to the development of next-generation manufacturing technologies. These facilities provide the infrastructure and resources necessary for experimenting with new design paradigms, such as additive manufacturing, digital fabrication, and sustainable manufacturing practices [22]. In this way, MDFs not only contribute to the advancement of manufacturing technology but also to the evolution of design thinking and methodologies within the manufacturing sector. Specifically, one of the primary functions of MDFs is to serve as testbeds for the practical application and validation of research findings. MDFs enable the real-world implementation of these technologies and methodologies, allowing for the assessment of their impact on manufacturing efficiency, hazard mitigation, and system resilience in a controlled yet realistic setting. For this reason, the research questions provided would benefit from testing in an MDF environment.

3. METHOD

This study employed a structured, remote design procedure to explore the design processes and hazard identification capabilities of professionals in a cyber-physical manufacturing environment. Utilizing a mix of digital tools for real-time collaboration and

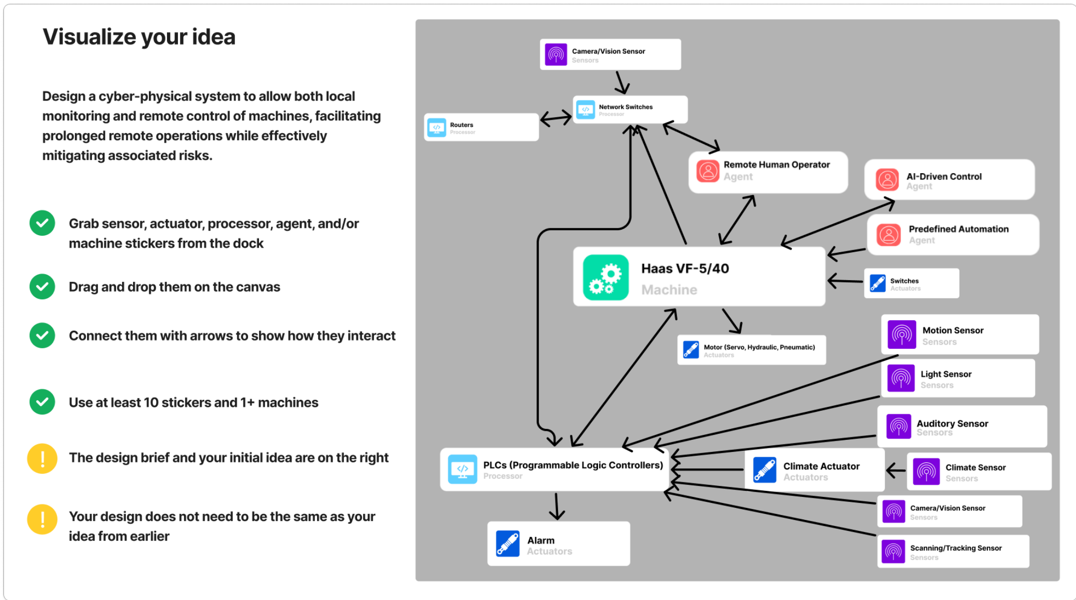

FIGURE 1: GRAPHICAL USER INTERFACE FOR TASK 2 (PARTICIPANT 2'S DESIGN SHOWN)

design visualization, the procedure was divided into five (5) key tasks, each aimed at progressively unfolding the participants' approach to conceptualizing, designing, and evaluating a cyber-physical system of their own design. This approach aimed to capture a comprehensive understanding of design strategies and risk assessment in complex manufacturing settings.

3.1 Procedure

Six (6) participants were engaged through convenience sampling, facilitated by a colleague at Oak Ridge National Laboratory's Manufacturing Demonstration Facility (ORNL's MDF). The sampling intentionally aimed to include participants who could provide a wide range of expert perspectives on the design tasks at hand. The participants were provided an optional 25-dollar Amazon gift card for their time and efforts volunteered. The cohort comprised a diverse mix of professionals, including three Mechanical Engineers and three Research Staff, with a broad age range of 21 to 50 years and varying levels of experience from 2 to 15 years. Educational backgrounds include two Bachelor's, three Master's, and one Doctorate degrees, with core backgrounds in Mechanical Engineering and Electrical Engineering. There were four male and two female participants.

The study was conducted remotely, utilizing Zoom for communication and screen/audio capture. A custom graphical user interface (GUI) was developed for the experiment in Figma. Each session was roughly one (1) hour, and various data types were collected. Demographic information was collected via Google Forms. Design rationale and think-aloud comments were collected through audio recordings, and written responses and digital diagrams were created and collected using the GUI.

Participants were guided through the conceptualization and visualization of a cyber-physical system for long-duration machining in a manufacturing environment, focusing on remote monitoring and control to mitigate associated risks. The procedural component of the study was structured into five (5) distinct tasks, each designed to simulate various stages of conceptualizing and designing a cyber-physical system within a manufacturing context. Before the first task, participants were primed with the following design brief:

> *"Your mission is to design a cyber-physical system for a manufacturing environment that does long-duration machining. Your solution should offer insights into machine operations and facilitate remote control that can mitigate risks associated with non-human attended long-duration machining. Production continuity with remote human-in-the-loop control should be possible. Your system should be designed to address the risks inherent to machine operation, including control access, materials, part production (manufacturing), machinery itself, adjacent machinery, personnel, and the manufacturing environment itself."*

Task 1 (Ideation, 5 minutes): This initial phase, facilitated through the GUI, tasked participants with conceptualizing a cyber-physical system optimized for long-duration machining tasks. The design brief emphasized the integration of real-time monitoring and remote control functionalities to proactively manage and mitigate operational hazards. Participants were encouraged to consider system responsiveness across diverse operational scenarios, mandating the inclusion of at least one primary long-duration machine alongside optional auxiliary machinery. The ideation outcomes were written by the participants within the GUI, providing a textual foundation for the subsequent design visualization task. This approach ensured that participants articulated a vision for their system.

Task 2 (Design Visualization, 20 minutes): With further instructions provided within the GUI, participants translated their ideations into visual designs. They were provided with an array of digital stickers representing five (5) processor options (Router, Microcontroller, PLC, Network Switch, IoT Hub), five (5) actuator options (Alarm, Motor, Solenoid, Climate Actuator, Switch), eight (8) sensor options (Button, Auditory, Motion, Pressure, Camera/Vision, Climate, Scanning/Tracking), three (3) machine options (Tormach 1100MX, Haas VF-5/40, Okuma MU-8000V), and four (4) agent options (Local Human Operator, Remote Human Operator, Predefined Automation, AI-Driven Control) [23–25]. Hovering over stickers revealed a description of the asset: e.g., *"Network Switches: connect devices, establishing a local communication network," "Alarms: visually or audibly alert remote or local operators of undesirable conditions, such as buzzers or LEDs,"* etc.. Participants were instructed to illustrate their system's architecture, focusing on component interconnectivity and overall system coherence. This visualization phase required a minimum of ten (10) stickers and one (1) or more machines, all connected by directional arrows encouraging a detailed portrayal of the system's functional and operational dynamics.

Task 3 (Hazard Identification – Un-Timed): Building on the visual designs, participants were prompted to identify and annotate potential hazards using a specific "hazard sticker" within the GUI . This phase was aimed at evaluating the participants' proactive risk assessment mentality. By pinpointing and documenting perceived risks, participants highlight the potential safety, security, and operational vulnerabilities inherent to their proposed systems.

Task 4 (Hazard Typology – Un-Timed): With hazards identified, participants engaged in a classification exercise, mapping each identified risk to one of six predefined hazard categories. This structured approach to hazard analysis was aimed at facilitating a comprehensive risk assessment. The six hazard types participants could choose from were:

Physical: *Bodily harm or injury to individuals (incl., respiratory, auditory, and ergonomic).*

Digital: *Compromise of data integrity and security (incl., data loss and breaches).*

Legal: *Exposure to litigation (incl., compliance and regulatory issues).*

Social: *Threats to social connections (incl., community and workplace relationships).*

Emotional: *Psychological distress or trauma experienced by individuals (incl., stress and anxiety).*

Environmental: *Impacts on manufacturing environment (incl., wastewater, toxic emissions, scrap disposal).*

Task 5 (Hazard Severity Rating): The concluding task involved assessing the severity of each identified hazard using a 5-point Likert scale within the GUI. This step allowed participants to prioritize risks based on their potential impact, reflecting current engineering practices where risk severity assessment plays a crucial role in shaping system design and safety measures.

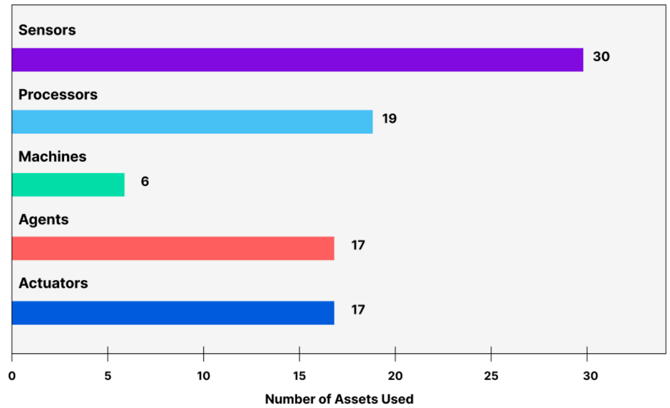

FIGURE 2: TOTAL NUMBER OF ASSETS USED BY ALL PARTICIPANTS SORTED BY ASSET TYPE

IRB and Informed Consent: Ethical compliance was ensured through IRB approval, with participants undergoing a thorough informed consent process detailing the study's nature, their rights, and confidentiality measures. All data were anonymized to maintain participant privacy, using alphanumeric identifiers for data attribution.

4. RESULTS AND ANALYSIS

This section presents the mostly quantitative results from tasks 1-5. However, when there were questions about the data, we turned to the transcript data to provide additional qualitative insights about the findings. Findings are presented across three key areas informed by the three RQs: the utilization of various design assets, the impact of initial design decisions, and the evolution of hazard identification over the course of the design tasks. An examination of these aspects aim to provide insights into the designers' strategies and challenges in recognizing potential hazards within the design environment.

4.1 Asset Utilization

Through examining the utilization of assets throughout the design tasks, this study aimed to understand how participants distributed and prioritized various assets, thereby revealing their strategies and approaches to navigating the complex design environment. The specific research question guiding this examination of asset utilization was:

RQ1: What does the distribution and prioritization of asset types indicate about design strategies for remote manufacturing monitoring systems?

The initial examination of asset distribution and usage highlighted a predominant preference for sensor assets, with a total of 30 instances of use, averaging 5 instances per participant (see Fig. 2). This was closely followed by processors, which were utilized 19 times in total, with an average of 3.17 uses per participant (see Fig. 2). Agents and actuators were equally favored, each used 17 times in total, averaging 2.8 instances per participant (see Fig. 2). Machines were the least utilized asset type, with only 6 instances

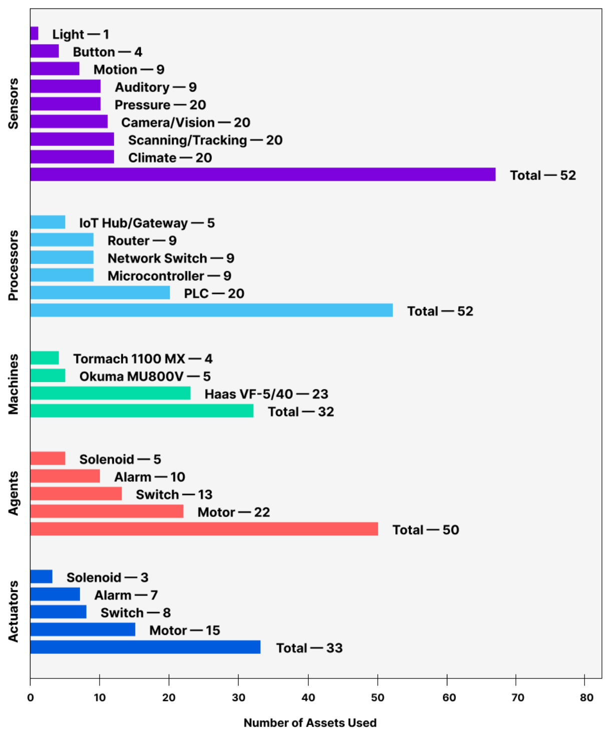

FIGURE 3: TOTAL NUMBER OF TIMES ASSETS WERE CONNECTED TO BY ALL PARTICIPANTS

of use, averaging 1 instance per participant (see Fig. 2). This distribution suggests a focus on sensing and processing capabilities in the initial design stages, potentially indicating a prioritization of information gathering and processing in managing the design complexity.

The variability in asset usage among participants, suggests diverse approaches to the design task. This diversity may reflect individual differences in tackling the design challenge, with some participants possibly emphasizing information gathering and analysis (as indicated by the higher use of sensors and processors), while others may focus on action and interaction within the design environment (as reflected in the use of agents and actuators) (see Fig. 2 and 3).

When looking at initial asset choices, as measured by the first three asset types used by participants—machines (10x), sensors (5x), actuators (3x), processors (1x), and agents (0x)—a similar preference for sensors emerges. This finding suggests that designers a focus on manufacturing technologies (machines) and situational awareness (sensors) in early design stages. Whereas, across the entire design process, their focus centers of situational awareness (sensors) and data processing/transfer (processors). This choice might indicate participants' attempts to mitigate uncertainty in the complex design space by prioritizing assets that provide information (sensors) and feedback (sensors and actuators) about the environment and the system's state.

The findings from the asset utilization analysis set the baseline for understanding participants' initial design decisions and strategies in navigating the complex design task. The focus on sensors and processors suggests an initial strategy oriented towards information gathering and analysis, potentially shaping subsequent design decisions and approaches to hazard identification.

4.2 Initial Design Strategies and Task Load Management

Through examining design decisions across the discrete tasks and thus temporally, we aimed to understand how participants managed their design choices of a complex system under limited time. The following research question guided this analysis of the quantity and variation of assets data:

RQ2: How do the quantity and variety of assets used reflect on participant cognitive load and strategic design focus?

The data revealed a notable trend towards simplification in machine selection across participants, despite the availability of multiple machine options. For instance, Participant 1 initially considered a more complex setup with three (3) machines in their written ideation, *"Automated robotic cell that works with multiple additional manufacturing cells (additive, subtractive, etc)."* During the visualization task they started by including all three machines, but decided to simplify to a single machine (Tormach 1100MX), remarking, *"I am going to simplify. I think I bit off more than I can chew."* This sentiment of scaling back due to perceived complexity or time constraints was mirrored in the choices of other participants, who all chose a single machine in their design visualization (task 2). Participants 2, 3, 4, and 6 each used only one machine, aligning with their initial ideation, while Participant 5, as described above, briefly considered two machines before also reverting to a single machine choice.

This uniform trend towards single machine use suggests a strategic prioritization of simplicity and manageability in the design process. Participants appeared to weigh the benefits of a more complex, potentially capable setup against the risks of overcomplication and the cognitive load of managing multiple machines. This decision-making process reflects an inherent balance between aspiration and pragmatism in design under constraints, highlighting the importance of manageability and feasibility in initial design decisions.

The reduction in machine variety also points to an underlying strategy of focusing on core functionalities and minimizing potential points of failure or complexity in the design. By concentrating on a single machine, participants could devote more attention to optimizing and integrating this core element into their design, rather than dividing their focus among multiple machines.

The implications of these initial design decisions due to design complexity are significant, suggesting that designers in complex manufacturing environments may benefit from strategies that allow for flexibility and iterative refinement. The tendency to simplify under pressure underscores the need for design processes that support gradual complexity management, enabling designers to adapt their strategies as the design evolves and more information becomes available.

4.3 Hazard Identification.

The exploration of temporal shifts in hazard identification aimed to uncover how participants' identification of hazards evolved throughout the design process, particularly in response

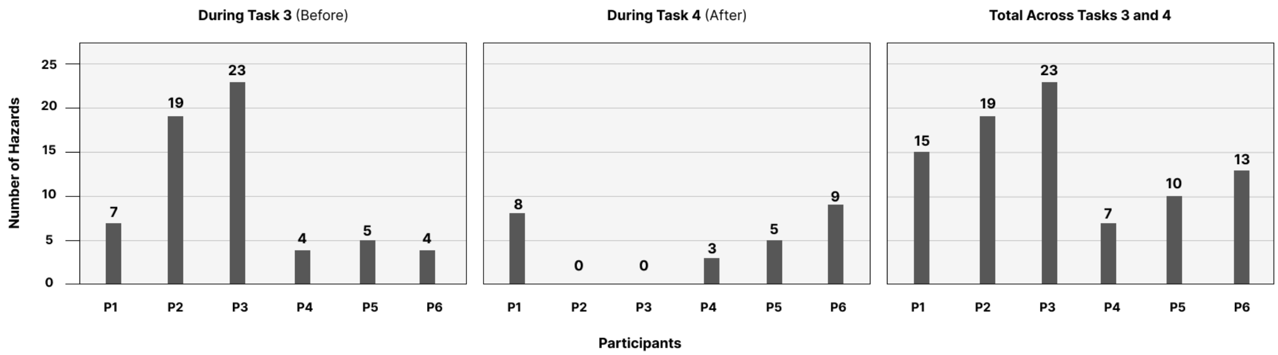

FIGURE 4: HAZARD IDENTIFICATION ACROSS TASKS (SORTED BY PARTICIPANT AND TASK)

to prompts and the progression of the design task. The following research questions guided this aspect of the analysis:

RQ3: How might the types and severity of hazards identified over time reflect participant intuition and perception of manufacturing hazards and design responsibility?

Hazards Identification Over Time. A key finding from this investigation was the notable increase in hazard identification following specific prompts within the design task. Most participants (4) added additional hazards in task 4 after being encouraged to label hazards in task 3, indicating that the hazard identification process is responsive to external cues or the depth of engagement with the design task (see Fig. 4). However, not all participants labeled additional hazards. This suggests that hazard identification is not merely a function of initial design analysis but evolves dynamically as designers engage more deeply with the task and are prompted to consider potential risks. These temporal shifts in hazard identification highlight the dynamic nature of risk assessment in design tasks, emphasizing the role of iterative review and external prompts in uncovering a broader range of potential hazards. It also underscores the need for design processes that incorporate regular reassessment and allow for the gradual refinement of hazard awareness, ensuring a comprehensive approach to risk management in complex manufacturing environments.

The types and severities of hazards identified also varied considerably, with a total of 87 hazards being flagged across all participants, averaging 14.5 per participant. The distribution of hazard types—Digital (25), Property (21), Physical (20), Environmental (7), Legal (5), Emotional (5), and Social (4)—highlights a broad spectrum of concerns ranging from tangible risks like Physical and Property damage to more abstract concerns such as Digital and Social implications (see Fig. 4). This diversity in hazard identification reflects the multifaceted nature of risks in complex manufacturing environments and underscores the importance of a comprehensive approach to hazard assessment.

Intuition vs. Exploration. In exploring hazard identification within the design process, a notable dichotomy emerged between intuitive and exploratory approaches, as evidenced by the participants' engagement with the task. Figures 4 and 5 shed light on this distinction, illustrating the number of hazards identified by participants both before and after specific prompts within the design task. Interestingly, those participants who perceived their initial hazard identification as comprehensive (P2 and P3) (see Fig. 4)—without the need for subsequent additions—exhibited a distribution of hazard severities that approached a normal distribution (see Fig. **??**). This contrasts with participants who adopted a more iterative approach, adding additional hazards and revisiting their hazard assessments from task 3 during task 4. These participants (P1, P4-6) also had severity ratings that were more akin to an inverted bell curve distribution, suggesting that they considered severity differently from P2 and P3 (see Fig. 5) This preliminary observation suggests a nuanced dynamic between the depth of initial hazard identification and the perception of hazard severity, hinting at a possible correlation between a designer's confidence in their initial assessment and their sensitivity to potential risks.

This intuitive versus exploratory dichotomy raises intriguing questions about the cognitive processes underlying design decision-making, particularly in complex environments where the scope and nature of potential hazards can be vast and varied. The iterative approach, characterized by refinement and reassessment, may foster a more nuanced understanding of the design space, potentially leading to a more comprehensive identification of hazards. Conversely, an intuitive approach, relying on initial assessments, may reflect a designer's confidence in their ability to foresee and account for potential risks from the outset. However, this confidence might also lead to oversight of less apparent hazards, underscoring the importance of balance and flexibility in design strategies.

Participant 2's remark,*"I guess if the alarms fail or the switches fail, if anything fails – oooph! I'm just gonna litter vulnerabilities all over this thing,"* encapsulates the growing awareness of potential hazards as the design process unfolds. This evolution in hazard awareness points to the significant impact of iterative review and external prompts in uncovering latent hazards that may not be apparent in initial design assessments.

Severity of Hazard Types. The analysis of hazard types and their perceived severities (see Fig. 5) unveils intriguing patterns in how different hazards are recognized and prioritized by designers. The mean severity across all participants is 3.25, and the standard deviation is 1.26. In this way, we see that participants tend to gravitate away from the tails of severity (not severe at all or the most severe).

Additionally, the data reveals that participants more read-

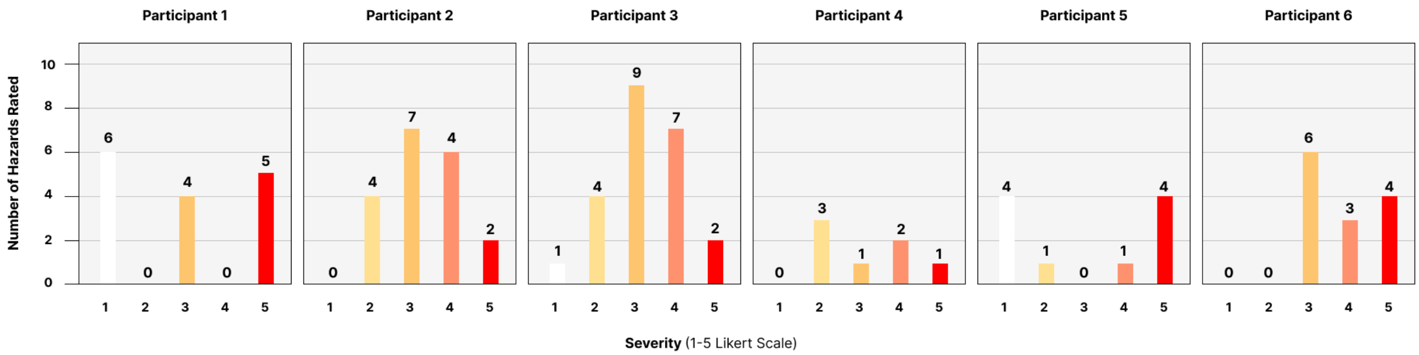

FIGURE 5: HAZARD SEVERITY DISTRIBUTION (SORTED BY PARTICIPANT)

ily identified Digital, Physical, and Property hazards were also often deemed to carry higher severity (see Fig. 5). This tendency suggests that hazards with more tangible or immediate implications on system functionality and safety are more likely to capture the designers' attention during the design process. In contrast, hazards classified under the Social, Legal, Emotional, and Environmental categories were less frequently recognized, potentially indicating a gap in the holistic assessment of risks that encompasses both technical, environmental, and/or socio-emotional dimensions (see Fig. 5).

Participant 6's insights from Task 1 resonate within this context. Their emphasis on simplicity—*"Too many sensors over complicate systems and make it difficult to service and keep running. Simple single purpose sensors that are resilient to failure are the backbone of the system I will design....Closing Thoughts: Simplicity is very important. When a system is too complicated operator complacency can increase and make for a dangerous environment."*—echoes the critical balance between system complexity and safety. This perspective not only acknowledges the inherent risks associated with 'overcomplication' but also signifies an early awareness of hazard implications that can manifest from the very inception of the design process.

This disparity in hazard recognition and severity assessment underscores the complexity of the design decision-making process, where subjective interpretations and personal experiences significantly influence risk perception. For instance, Participant 5's reflection on predefined automation–*"predefined automation has social and emotional distress... that stress lives with you forever"*—underscores the emotional and psychological dimensions of hazard identification. This insight highlights the personal and subjective aspects of design decision-making, where designers not only consider technical and functional risks but also grapple with the personal and social implications of their design decisions.

5. DISCUSSION

The intricate dynamics of hazard detection and identification underscore the iterative nature of hazard identification, participants' subjective perceptions of risk, and the challenge of managing high dimensional systems design and their high volume of safety needs. These themes highlight the nuanced interplay between design complexity, safety considerations, and the cognitive load on designers, offering insights that could inform future design methodologies and tools in manufacturing and beyond.

Hazard Detection and Identification. Hazard identification emerged as a highly dynamic aspect of the design process, influenced significantly by the progression of the design task and specific prompts. While the task was imagined with one hazard identification stage (task 3), participants demonstrated an iterative approach to identifying hazards, with their awareness of potential risks seemingly evolving as they encountered tasks 4 and 5. This additive outcome suggests that hazard identification is not a one-time activity but a continuous process that benefits from regular reassessment and additional prompting.

The complexity of adding multiple systems to a design was a recurring theme, highlighting the cognitive load and potential for overcomplication faced by designers. This complexity underscores the need for design strategies that balance comprehensive hazard identification with manageable system integration.

Such reflections illuminate the nuanced and multifaceted nature of hazard identification, where designers must navigate the delicate interplay between ensuring system robustness and avoiding unnecessary complexity that could inadvertently elevate the risk of hazards. Simplicity and clarity should be foundational principles embedded into the design process, promoting designs that are both functionally effective and inherently safer, thereby aligning with the principles of human-centered design in complex manufacturing environments.

Attitude Towards Hazards. A nuanced subjective perception of risk and severity characterized participants' attitudes toward hazards. The severity assessment of different types of hazards—digital, physical, social, etc.—revealed varied levels of recognition and concern among participants. Notably, tangible hazards such as physical and digital risks were more readily identified and deemed of higher severity, suggesting a possible prioritization of immediate, functional risks over more abstract concerns. This discrepancy in hazard recognition underscores the fact that not everyone comes with the same frame for what risks are nor what the impact of any given risk is. This itself begs us to consider the importance of research-based approaches to hazard assessment, ones that strive to encompass the full spectrum of potential risks, including those that may not be immediately apparent, as well as ground truths on the severity of any given risk.

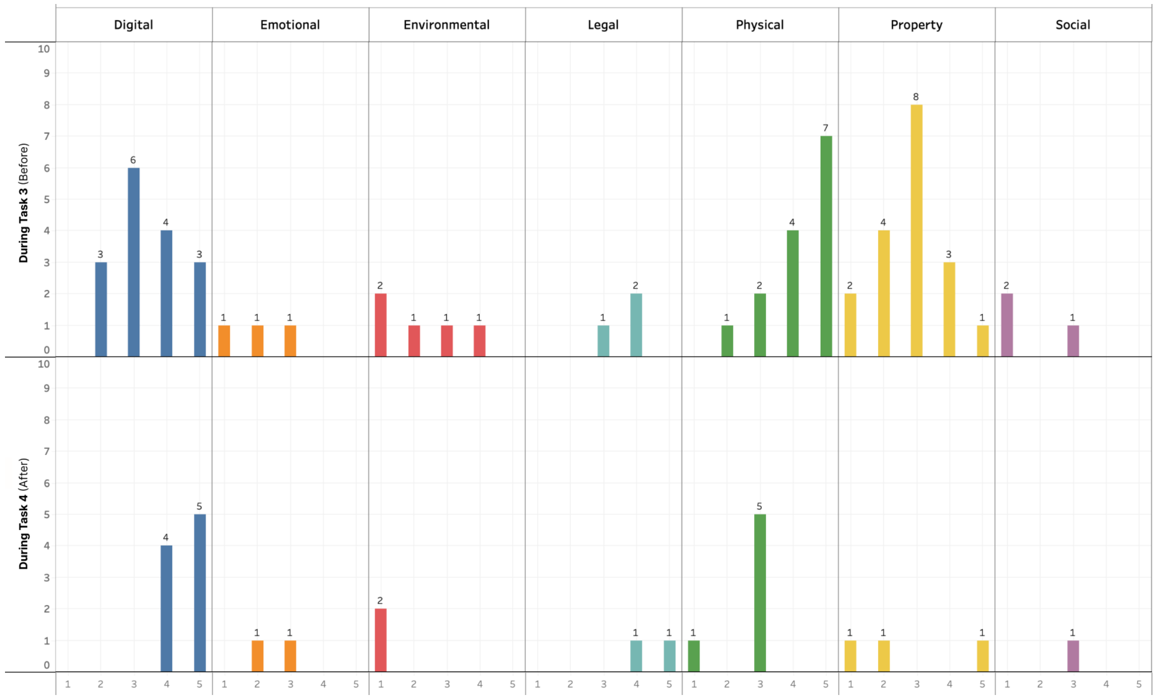

FIGURE 6: HAZARD TYPE (SORTED BY SEVERITY AND TASK)

Overload of Safety Needs. The volume of safety needs and the associated complexity of addressing them were significant challenges for participants, particularly when considering the integration of multiple systems. The desire to add various mechanisms was often tempered by realizing the inherent complexity such additions would entail and, thus, the implicit expanded risk surface area. This finding points to a critical tension in design decision-making: the need to ensure comprehensive safety coverage while maintaining a feasible and manageable design. Designers must navigate this tension, making strategic decisions about which safety needs to be prioritized and how to integrate them effectively without overwhelming the design or the designer.

Surprisingly, qualitative insights also demonstrated that participants considered risk not only as an outcome that could be experienced by the system or its users but also by the designers responsible for the ensuing design. This finding reminds us that the design process itself—not just the ensuing design—is riddled with risk, and designers themselves are aware of this fact.

Implications for Design Processes. The insights gleaned from this study have implications for design processes for complex systems, especially for manufacturing environments. To manage design complexity and enhance hazard awareness, designers could benefit from iterative design strategies that allow for regular reassessment of hazards. Furthermore, developing design tools that support complex decision-making and provide enhanced visualization of hazards could significantly aid designers in managing the volume of safety needs and system interconnectedness.

6. CONCLUSION

In conclusion, this study illuminates the intricate process of hazard identification within the design phase of complex manufacturing environments, highlighting the pivotal role of initial design decisions and the design stage in recognizing potential hazards. The findings emphasize the necessity of extended, iterative design processes and strategic planning from the outset to improve hazard identification capabilities. Future research should aim to expand the scope to include various machine types and refine research methodologies to capture the nuances of multi-system interactions, thereby enriching our understanding of design strategies and their impact on safety in manufacturing settings. Enlarging the sample size and diversifying participant demographics will further enhance the robustness of these insights, contributing to the development of more effective design support tools and safer manufacturing practices.

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