

Informing Engineering Education Through Industry: A Survey of Situation Awareness in Manufacturing Practice

Mr. EDWARD JAMES ISOGHIE, University of Louisville

Edward Isoghie is a PhD candidate with a research focus on human factors and engineering education leveraging emerging technologies such as AI, digital twin, and virtual reality. He obtained his bachelor's and master's degrees in Industrial and Production Engineering from the University of Ibadan, Nigeria, and a masters in Operations Management at the University of Alabama, Tuscaloosa.

Jason J Saleem, University of Louisville

Jason J. Saleem is an Associate Professor with the Department of Industrial Engineering at the J.B. Speed School of Engineering at the University of Louisville. He is also a Co-Director of the Center for Human Systems Engineering (CHSE). Dr. Saleem received his Ph.D. from the Department of Industrial and Systems Engineering at Virginia Tech in 2003, specializing in human factors engineering and ergonomics. Dr. Saleem's research interests focus on the integration of human factors engineering with the development of health information technology (HIT). His research also focuses on provider-patient interaction with respect to exam room computing, as well as virtual care tools and applications. Dr. Saleem also maintains an engineering education research portfolio and in 2024 was awarded a grant by the National Science Foundation (NSF) entitled, 'Introducing a Mixed-Methods Approach to Engineering Students through Human-Centered Design'.

Informing Engineering Education through Industry: A Survey of Situation Awareness in Manufacturing Practice

Abstract

Modern manufacturing systems require workers to make rapid, informed decisions in dynamic environments. As technologies such as automation, robotics, and digital twins reshape the shop floor, the need for high situation awareness (SA) has become a vital non-technical skill. Despite its importance, SA is rarely addressed explicitly in engineering education or workforce development. This study aims to identify the SA skill needs of today's manufacturing professionals and translate those insights into actionable recommendations for preparing future engineers. We developed a survey to explore how SA is applied in manufacturing practice, to examine how SA skills are developed, to reveal SA skill gaps among newly graduated engineers, and to understand how industry professionals consider SA competencies essential for daily operations and future workforce readiness. The survey is structured around Endsley's three-level SA model: perception, comprehension, and projection, and includes items on cognitive factors, training and learning, and contextual applications of SA skill. Participants include professionals from various manufacturing sectors and job roles and professional networks. Results indicate that SA development is primarily mentorship-driven, with high perceived training effectiveness and strong confidence. Newly graduated engineers were reported to struggle mostly with interpreting system behavior and anticipating future states. Respondents identified anomaly detection, system understanding, and predictive reasoning as essential competencies in manufacturing contexts. The results underscore the need for curriculum development aimed at enhancing SA skills in engineering education. By linking practical industry needs to educational design, this study seeks to help bridge the cognitive skills gap between the classroom and the manufacturing environments.

Introduction

The historical trajectory of manufacturing, from the mechanical looms of the first industrial revolution to the data-driven ecosystems of the present, has been characterized by a relentless pursuit of efficiency. The Fourth Industrial Revolution (Industry 4.0) introduced smart technologies such as artificial intelligence (AI), cloud connectivity, and real-time data analytics into manufacturing and supply chains, transforming labor-intensive operations into digitally connected cyber-physical systems to drive productivity. This evolution led to human out-of-the-loop, reshaping workforce roles, shifting human responsibilities toward supervisory, monitoring, and decision-making tasks while interacting with automated, real-time intelligent systems. The Fifth Industrial Revolution Industry 5.0 builds on this transformation, positioning human workers at the core of the production process and emphasizing efficient collaboration between humans and machines within digital ecosystems [1], [2]. Moreover, the emergence of Industry 5.0 introduces the necessity for Shared Situation Awareness (SSA) between human workers and intelligent agents. Unlike traditional industrial robots that operated in isolation behind safety cages, modern cobots share the workspace, requiring a mutual understanding of intent and future movement [3], [4].

Manufacturing systems have evolved into highly dynamic sociotechnical environments characterized by advanced automation, digital integration, and increasing cognitive demands on human operators. Engineers and technicians are now required to coordinate across complex workflows involving machines, software systems, data streams, and multidisciplinary teams. As manufacturing systems become more complex and dynamic, technical competence alone has become insufficient and acquisition of non-technical skills (NTS) has become essential to keeping pace with emerging technologies and evolving skill demands [5]. Consequently, upskilling and reskilling have become central pillars of contemporary workforce development. Technical skills have been the focus of vocations and training of engineers. Skills other than technical competencies are also recognized as essential in manufacturing. Most serious adverse events in manufacturing are related to non-technical skills (NTS) failures. This has fostered interest in teaching manufacturing professionals about non-technical skills [6], [7]. NTS varies, however, these NTS can be divided into two main categories: social skills (communication, teamwork and leadership) and cognitive competences (situation awareness, decision-making) [8], [9], [10], [11].

Situation awareness (SA) is a non-technical skill that plays a crucial role in various high-risk environments, including healthcare, emergency management, aviation, and military operations[12], [13], [14], [15], [16] and has gained increasing attention in the context of manufacturing practice. SA refers to an individual's ability to perceive elements in the environment, comprehend their meaning, and project future status[17], [18], [19]. SA plays a vital role in ensuring safety, efficiency, quality, and resilience in manufacturing operations. The importance of SA in manufacturing is underscored by its impact on operational outcomes. A lapse in SA can lead to accidents, production delays, and compromised product quality. For instance, an operator who fails to notice a subtle change in machine behavior may inadvertently cause equipment damage or a safety incident. Similarly, supervisors who lack a comprehensive understanding of the production environment may make decisions that negatively affect workflow and resource allocation [20], [21].

Although SA has been widely examined in other complex domains[15], [22], [23], [24], [25], it remains under-explored in manufacturing[26] especially from an engineering education perspective. Engineering education continues to emphasize analytical, problem solving, and technical skill, yet manufacturing practice requires continuous monitoring, sense-making, and cognitive ability in real time. As a result, graduates may enter manufacturing roles technically prepared yet under equipped to manage the demands of modern production environments. To better align engineering education with industry needs, there is a need to understand the use of SA in manufacturing practice. The goal of this study is to explore the concept of SA as a non-technical skill in manufacturing practice, examine its role in promoting safe and efficient operations, and highlight the need for training interventions. This work-in-progress paper aims to provide insights for industry stakeholders, educators, and researchers interested in advancing non-technical skill development in manufacturing. This research seeks to bridge the gaps between industry expectations and current engineering curricula. Specifically, it investigates (1) how SA skills are developed and perceived in terms of preparedness, (2) which SA skill gaps are observed among newly graduated engineers, and (3) which SA competencies industry professionals consider essential for daily operations and future workforce readiness. The scope of the study centers on translating practitioner perspectives into actionable guidance for engineering educators seeking to align instruction with the cognitive and operational

realities of modern manufacturing. Ultimately, this work contributes to recommendations for preparing future engineers to navigate complex production systems.

Related Works

SA has been extensively researched and applied in several high-stakes domains beyond manufacturing, the notably aviation, military, healthcare, and driving. In aviation, SA is considered a cornerstone of pilot performance, with studies showing that lapses in SA are a leading cause of accidents and incidents. Pilots must continuously monitor their environment, interpret instrument data, and anticipate changes in flight conditions to ensure safety [18], [27]. In the military, SA is critical for mission success, as soldiers and commanders must process [16], [28] vast amounts of information, recognize threats, and make rapid decisions under pressure [29], [30]. Training programs in both aviation and the military often incorporate simulation and scenario-based exercises to enhance SA and decision-making skills. In healthcare, particularly in surgery and emergency medicine, SA enables clinicians to detect subtle changes in patient status, coordinate with team members, and prevent errors [13], [31], [32], [33], [34], [35]. Research has shown that improved SA among healthcare professionals leads to better patient outcomes and reduced adverse events. Similarly, in the context of driving, SA is essential for hazard perception, navigation, and accident avoidance. Drivers with higher SA are better equipped to anticipate and respond to potential dangers on the road[23], [36]. This underscores the importance of SA as a non-technical skill and highlights the value of training interventions to develop and maintain high levels of SA in complex, dynamic environments.

As organizations across industries pursue digital transformation, the integration of SA training with broader organizational systems has become increasingly important. Digital transformation involves the adoption of advanced technologies such as the Industrial Internet of Things (IIoT), artificial intelligence (AI), and cloud-based platforms to enhance operational efficiency, data-driven decision-making, and overall competitiveness [20]. In this context, SA training must evolve to align with new workflows, technologies, and organizational structures. Within manufacturing contexts, existing studies focus on designing for SA rather as a skill. As a result, SA-related challenges in manufacturing are frequently discussed embedded within broader discussions of safety incidents, quality failures, or production disruptions. More recent work has expanded this scope to include cognitive ergonomics, particularly in response to increasing automation and digitalization. Studies examining manufacturing systems highlight issues such as information overload, complacency, human-out of the loop, and difficulties in maintaining a clear understanding of system behavior when control is shared between humans and machines[20], [37], [38], [39], [40].

Extensive work has been done in health education to expose students to NTS especially SA skill [41], [42], [43]. Engineering education research has acknowledged the importance of NTS, including communication, teamwork, and system thinking. However, SA is rarely addressed explicitly as a NTS. This study addresses this gap using a survey-based approach to capture industry perspectives on SA skill in manufacturing. This paper seeks to offer an integrative view that links SA demands in practice to the preparation of future engineers.

Methodology

This Institutional Review Board (IRB)-approved study explores the application of SA, a NTS in the manufacturing industry with a focus on promoting SA skill training in manufacturing education in preparing future engineers. This study adopts a survey-based research design to explore the industry relevance of SA as non-technical skill in manufacturing practice. The survey is structured around Endsley's three-level SA model: perception of relevant information, comprehension of system states, and projection of future conditions to reflect key dimensions of SA [18], [44]. First, the survey was reviewed by four human factors, a manufacturing expert and an educationist to ensure face validity. The sections include contextual application of SA, training and learning, factors that enable and hinder the three level of SA, and cognitive factors such as attention, working memory, and mental models. The final survey starts with participants providing their demographic background (job role, years of experience, manufacturing industry). A quantitative part of the survey asked participants structured closed-ended questions to understand contextual application of SA skill, state of training needs, cognitive factors affecting SA and shared SA in the concept of human-robot collaboration. The quantitative part also contained responses collected on 5-point Likert type scales. The qualitative part of the survey is designed to collect open-ended questions to understand scenarios on the application of SA skill. The instrument was designed for completion within approximately 25 minutes. Specifically, this study focuses on the training and learning section of the survey with the goal of determining existing SA training and effectiveness, identify SA skill gaps among new engineers, and essential and future-ready SA competencies for manufacturing practice. The survey section for this study combined multi-select, Likert-scale, and open-ended items to capture both structured quantitative data and contextualized professional insights from industry practitioners.

Study participants and data collection

Participants for this study include professionals from various manufacturing sectors and job roles and professional networks in the United States. Participants must be employed in a manufacturing related role such as production, engineering, safety, maintenance, or quality assurance to be eligible for the study. The study begins when a participant receives a recruitment invitation via email, which includes a brief explanation of the study. Participants receive an unsigned consent document, from which participants with continued interest, after consent document review, then proceed to complete the survey. The study aims to recruit approximately 20 to 50 participants. The survey is currently being administered through Microsoft form secure platform. Data collection will occur over a four-month period. Participants received an invitation containing a study overview and assurances of confidentiality in accordance with ethical standards. Responses will remain anonymous, and no personally identifying information is collected.

Data Analysis

Data analysis for this study follows a mixed-methods approach that integrated quantitative and qualitative insights to generate a comprehensive understanding of training of SA as a NTS in manufacturing practice. Quantitative data were analyzed using descriptive statistics. Multi-select responses were analyzed using selection frequencies and percentages. Open-ended responses were examined using thematic analysis to identify recurring patterns and higher-order competency themes. This mixed-format survey design enabled triangulation between training exposure,

perceived preparedness, observed SA skill gaps, and needs for future engineers, providing evidence-based insights for engineering education and workforce development.

Results and Discussion

A total of 19 participants has responded to the survey to date. The demographic results describe the background of the survey respondents in terms of job role, manufacturing experience, industry, organization size, location, and primary work area. As shown in Figure 1, the respondents were primarily engineers and supervisors, with additional representation from quality, safety, laboratory, ergonomics, and operator roles. In terms of manufacturing experience as depicted in Figure 2, the sample included both early-career and experienced workers, with the largest group reporting over 9 years of manufacturing experience. Respondents represented a range of industries, including food processing, automotive, appliances, aerospace, energy, chemical, electronics, design, molten metal production, and metal filtration. As shown in Figure 3, most respondents worked in larger organizations, particularly those with 501 or more employees. The respondents were mainly located in Louisville, Kentucky, although additional responses came from North Carolina, Ohio, Alabama, Florida, Indiana, Michigan, Georgia, and Texas. Most respondents worked on the assembly line or in quality/testing areas, with others working in safety, production, office, and high-test automation environments. The results are presented according to the three research questions: (1) training and preparedness, (2) observed SA skill gaps among newly graduated engineers, and (3) essential SA Skills for workforce readiness in manufacturing.

Training and Preparedness

Figures 4, 5, 6 and 7 shows the analysis of the multi-select training methods, training effectiveness, and anticipated need and confident level of SA skill in the industry respectively. Analysis of the multi-select training methods item showed that on-the-job mentorship was universally reported (95%), making it the dominant approach for developing SA skills in manufacturing settings. These findings indicate that SA development is primarily experiential and embedded within real operational contexts rather than delivered through formalized training programs. The heavy reliance on mentorship suggests that tacit knowledge transfer plays a central role in SA acquisition. As shown in Figure 5, most respondents viewed their SA training effectiveness. The result suggests that although training is largely informal and mentorship-driven, it is perceived as functionally effective in preparing engineers for SA requirements. Likewise, as shown in Figure 6 and 7, 68.4% agreed and 26.3% strongly agreed that they felt confident in their SA skills of respondents and all respondents universally acknowledged the necessity of SA skills. This indicates that all respondents recognized the importance of SA skills, suggesting strong understanding of their relevance in manufacturing contexts. Although on-the-job mentorship emerged as the dominant training method, structured approaches such as simulation-based training were comparatively limited. This reliance on experiential learning may suggest that SA skill development is largely informal, embedded within operational exposure rather than systematically designed within organizational training frameworks. While perceived effectiveness was high, the absence of standardized instructional models raises questions about consistency, scalability, and transferability across organizations.

From a broader perspective, the findings reinforce that SA is not automatically acquired through technical instruction alone. Instead, it appears to develop through guided experience, tacit

knowledge transfer, and contextual immersion. The high levels of reported confidence indicate that engineers eventually adopt SA competencies; however, this development may occur reactively rather than proactively. If SA training remains predominantly mentorship-based, variability in mentor expertise and learning environments may lead to uneven skill development among early-career engineers. In addition, for manufacturing systems that increasingly rely on real-time data, automation, and complex human-machine interactions, such informal training structures may become insufficient. Organizations may need to transition from implicit skill training toward more deliberate SA training frameworks that incorporate structured scenario-based learning, simulation, and reflective practice. Standardizing SA training could enhance safety, decision quality, and system resilience.

In engineering education, these findings suggest that SA should not be deferred entirely to workplace learning. Instead, pre-professional curricula should explicitly introduce students to the cognitive demands of dynamic systems, anticipation of operational disruptions, and system-level reasoning. Embedding SA earlier in the educational pipeline could reduce reliance on post-entry experiential learning and improve early-career readiness. Ultimately, recognizing SA as a core non-technical competency shifts workforce preparation from purely technical mastery toward holistic cognitive preparedness in modern manufacturing environments.

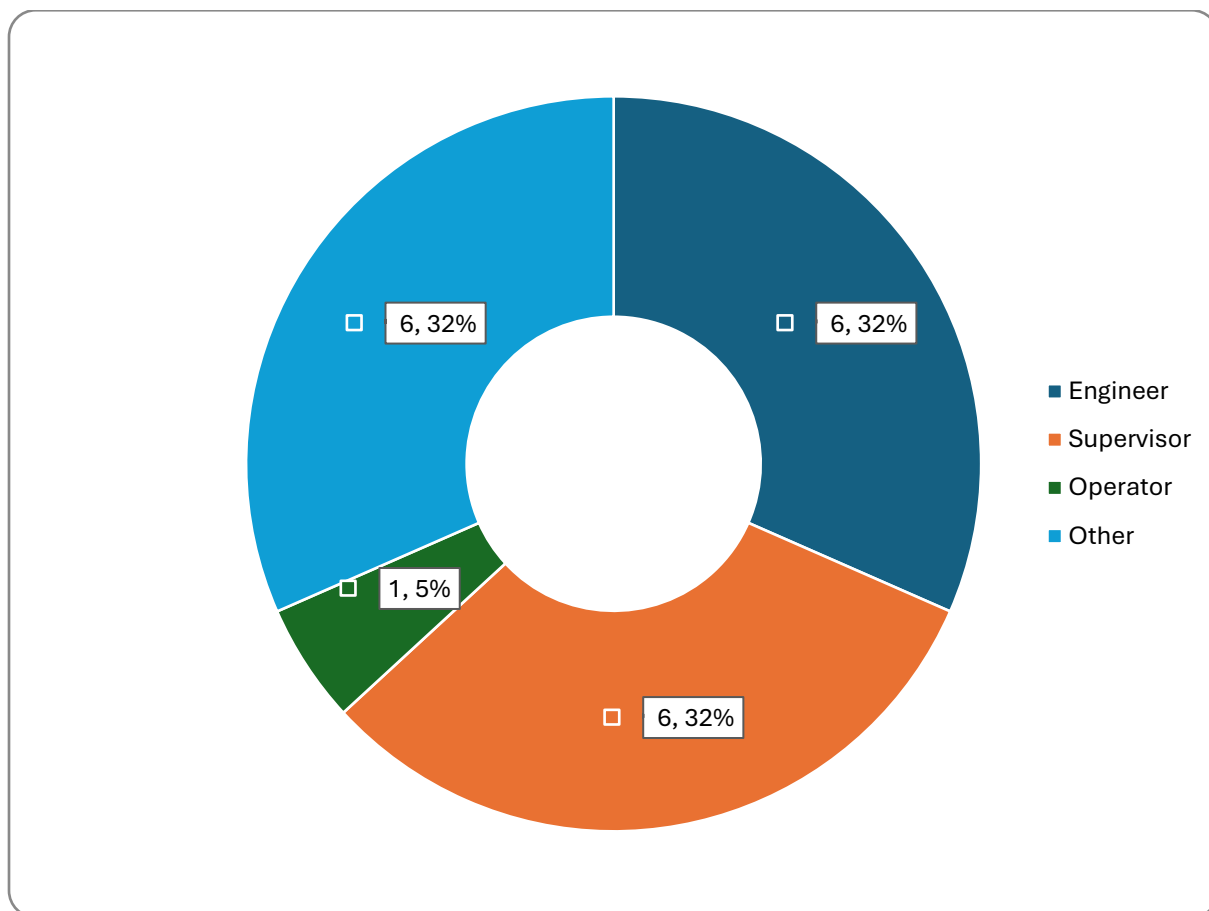


Figure 1: Job Title/Role Distribution

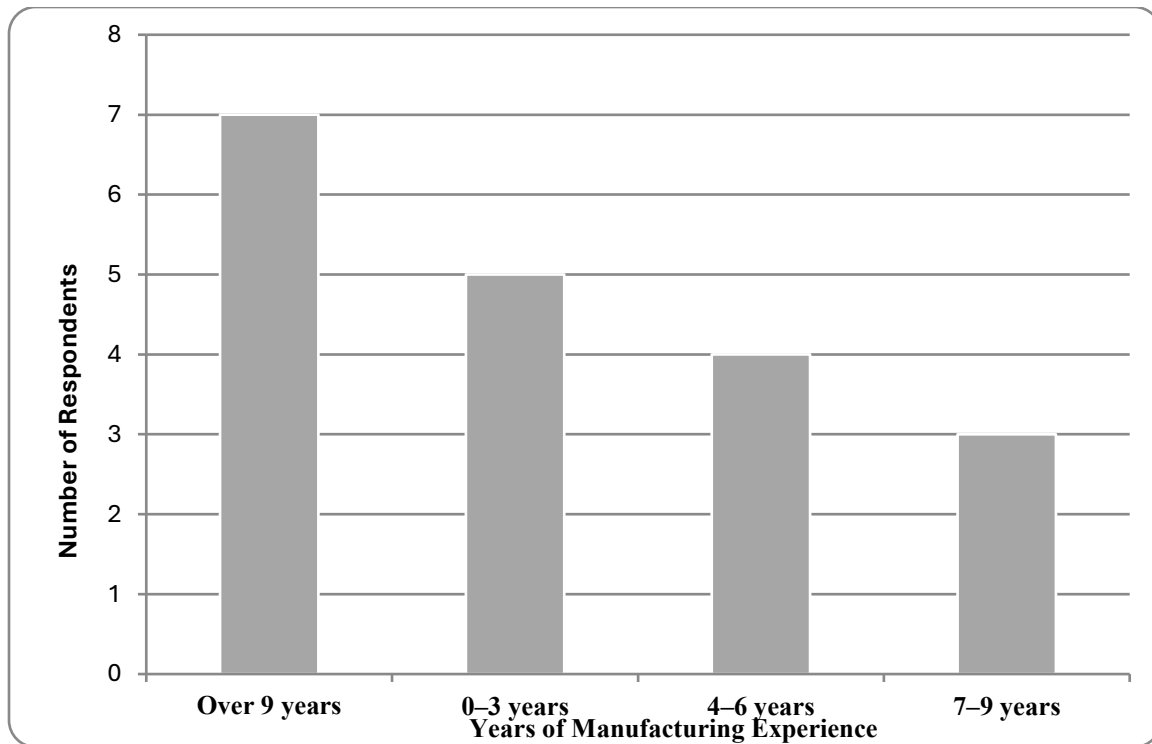


Figure 2: Years of Manufacturing Experience

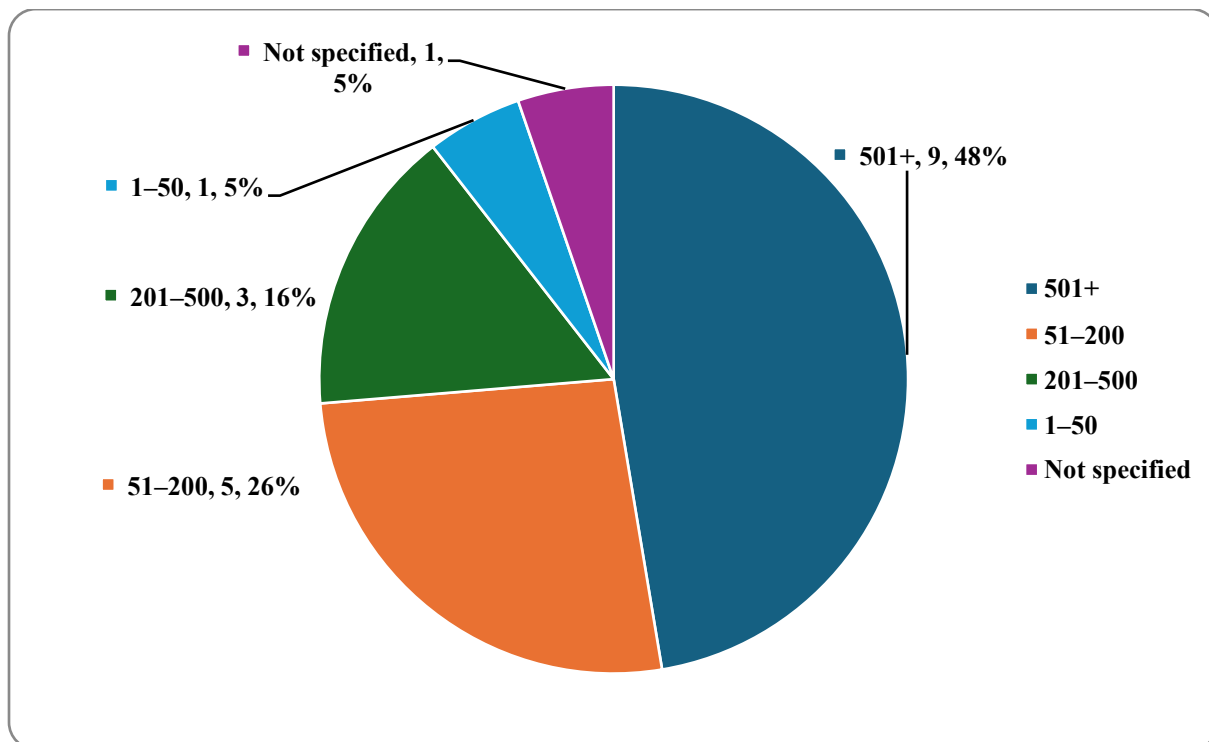


Figure 3: Company Size Distribution

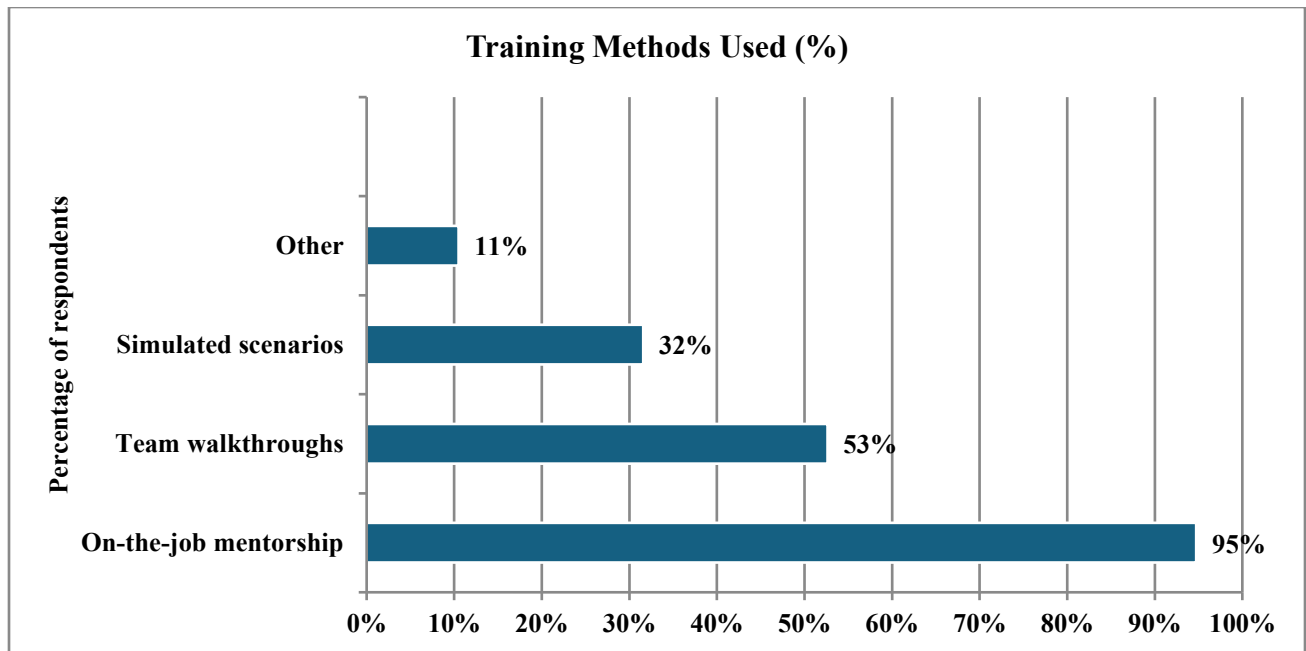


Figure 4: Training Method

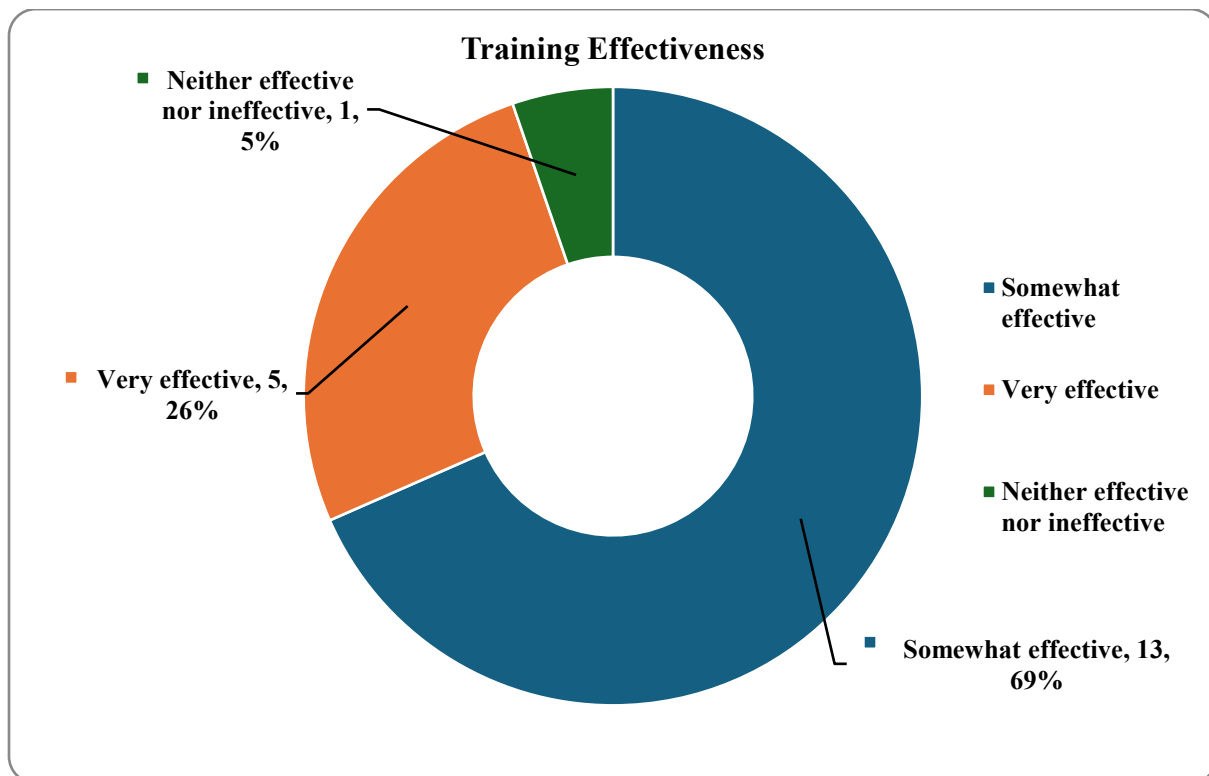


Figure 5: SA Training Effectiveness

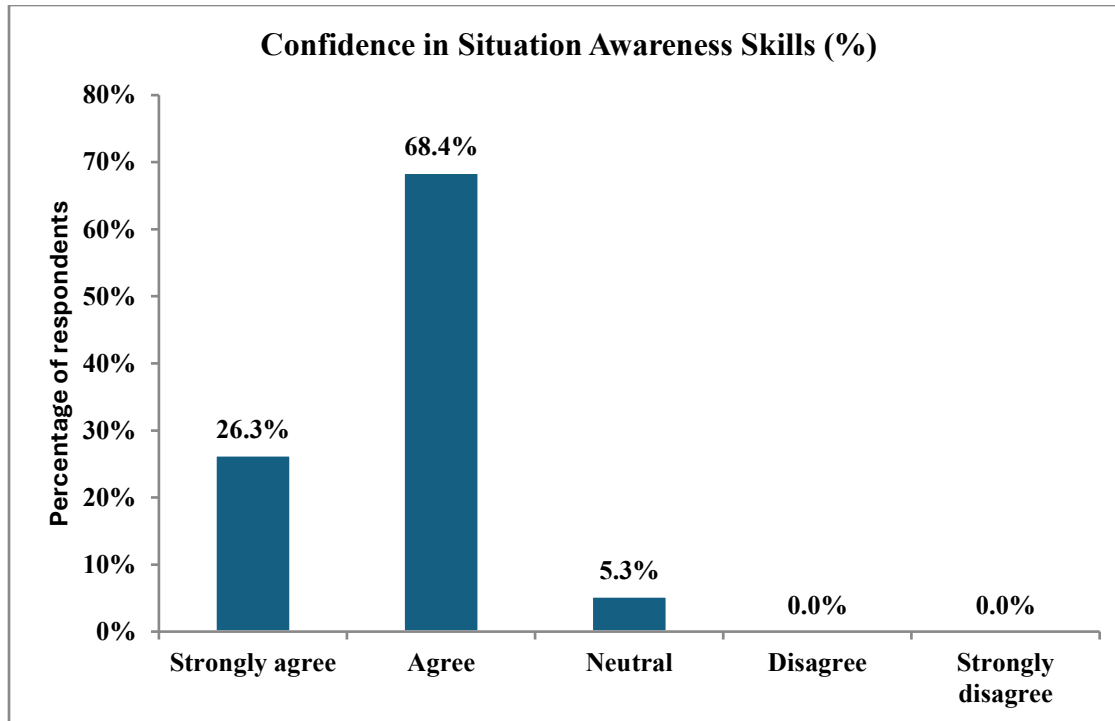


Figure 6: Confidence in Situation Awareness Skill

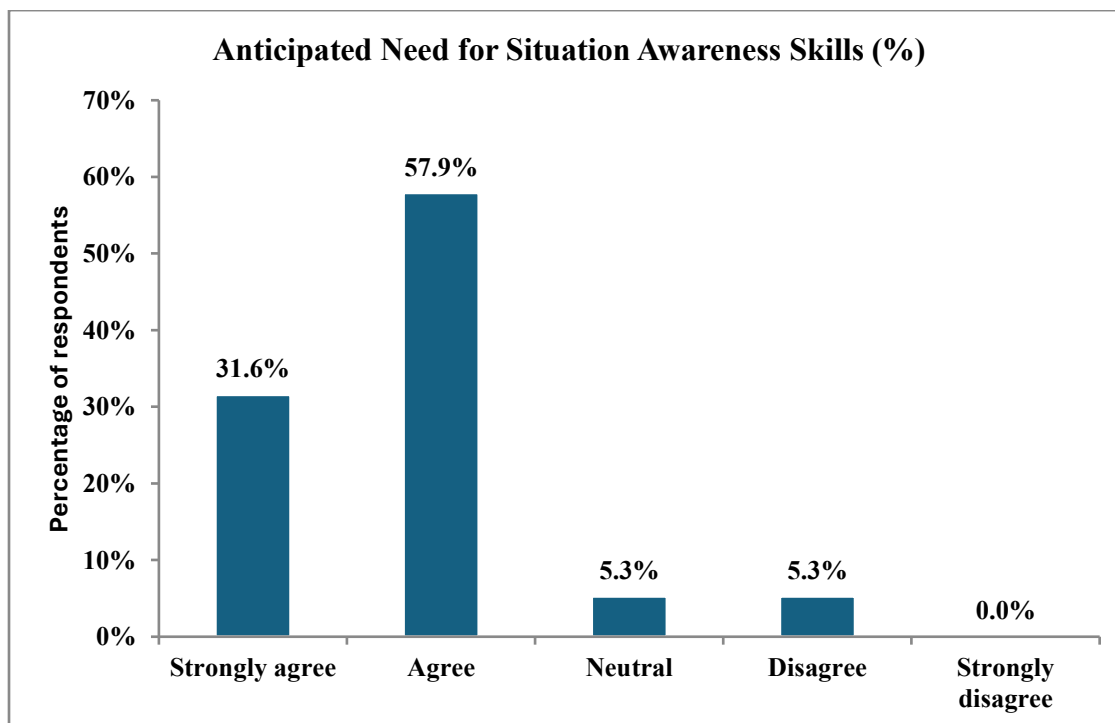


Figure 7: Anticipated Need for Situation Awareness Skill

Observed Skill Gaps

As shown in Figure 8, nineteen industry professionals responded to the multi-select item examining SA skill gaps among newly graduated engineers. These results suggest that new engineers may experience difficulty across multiple levels of SA. They may struggle to notice relevant system cues, understand the meaning of those cues, and predict future process states. Respondents emphasized

limitations in nuanced or specialized machine and process knowledge, difficulty understanding how humans interact with new systems, and a tendency for new engineers to focus on isolated defects rather than progressing toward short-term and long-term trend analysis. Several comments highlighted that early-career engineers “stop at a single defect” and struggle with broader system-level reasoning and forward-looking problem solving. These findings demonstrate the primary challenge lies in advancing from observation to interpretation and projection. The convergence of structured responses and qualitative elaboration suggests that newly graduated engineers struggle most with system integration, anticipatory reasoning, and next-level analytical thinking required for proactive manufacturing operations.

The result reinforces the position of SA as a foundational non-technical skill in manufacturing. Although technical proficiency remains essential, findings demonstrate that the most significant early-career deficiencies are not related to operating tools or understanding procedures, but to interpreting system behavior, anticipating failure modes, and synthesizing information across dynamic environments. This underscores that manufacturing performance depends heavily on NTS competencies that extend beyond traditional engineering curricula. Furthermore, in contemporary manufacturing systems characterized by automation, human-machine interaction, and real-time data flows, SA functions as the cognitive backbone of safe and efficient operations. More broadly, positioning SA as a measurable non-technical skill elevates its status alongside communication, teamwork, and leadership in workforce development frameworks. As manufacturing transitions toward increasingly interconnected and intelligent systems, engineers who possess strong SA may be better equipped to manage uncertainty, support safety, and drive operational resilience. Integrating SA development into engineering education therefore represents not only a pedagogical improvement but a strategic investment in manufacturing sustainability and competitiveness.

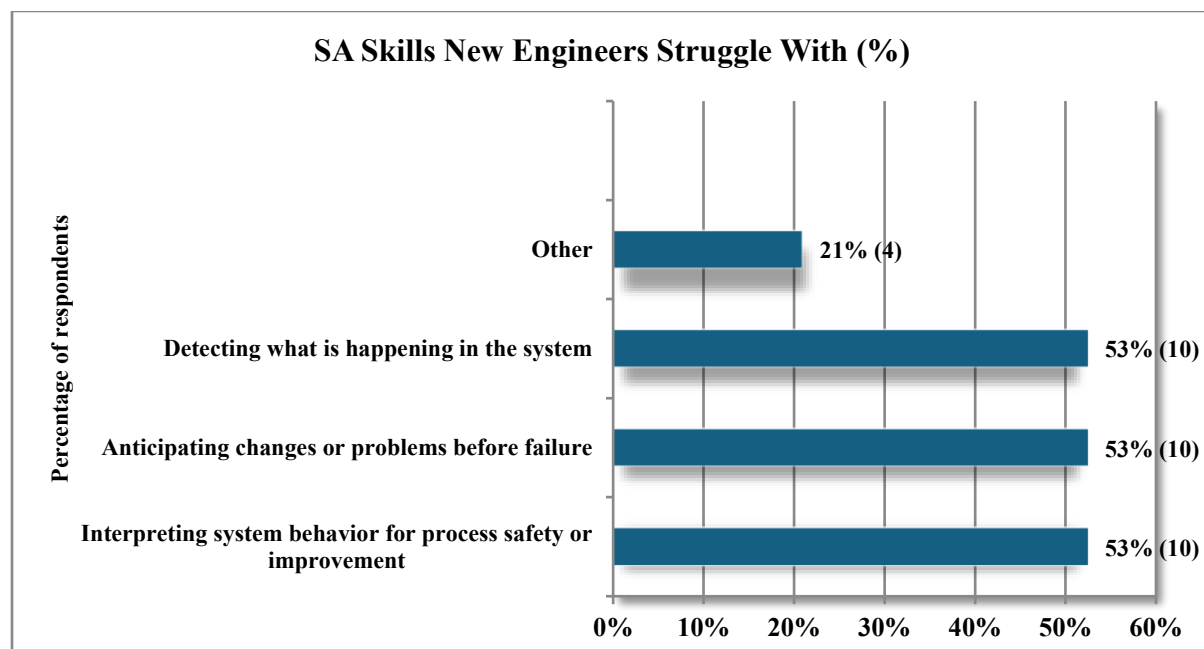


Figure 8: SA Skills New Engineers Struggle With

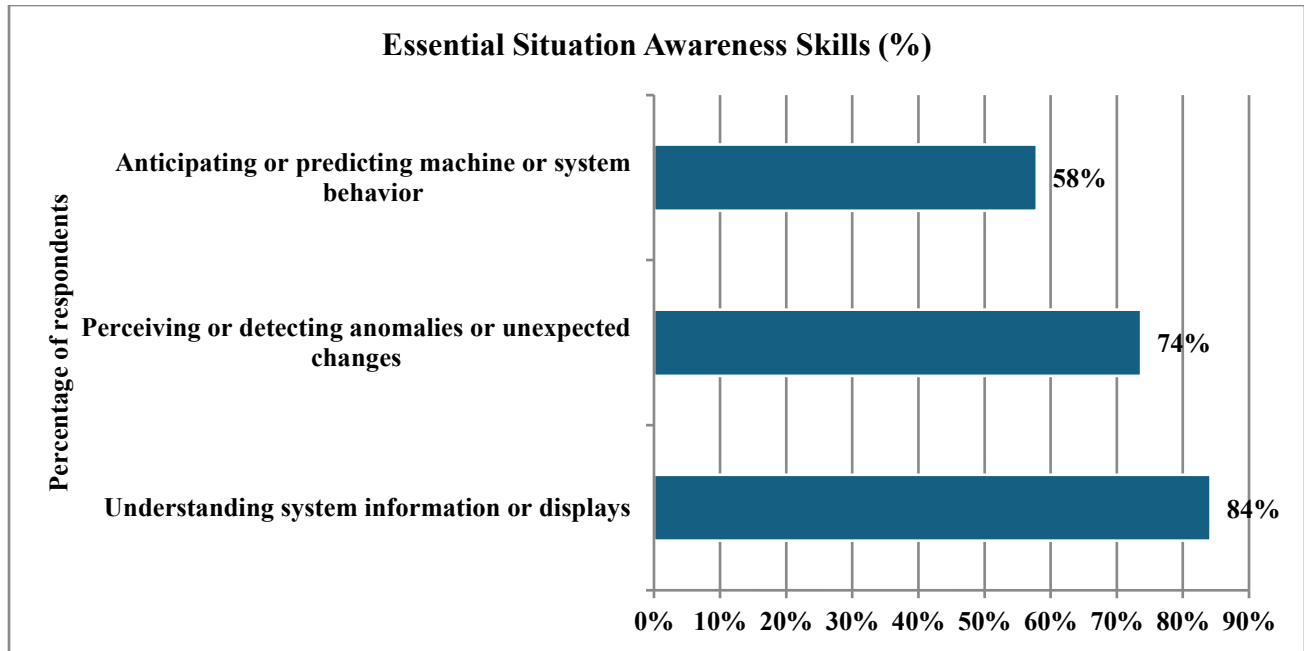


Figure 9: Essential SA Skills New Engineers

Essential Situation Awareness Skills for Workforce Readiness in Manufacturing

Industry professionals responded to the multi-select question and an open-ended question assessing which SA skills are most essential for daily work and future manufacturing workforce readiness. Result from the nineteen (19) participants showed strong endorsement of core SA competencies. As depicted in Figure 9, perceiving or detecting anomalies or unexpected changes was selected by 74% of the respondents, indicating that attentional monitoring and rapid recognition of deviations are viewed as fundamental requirements in manufacturing environments. In addition, understanding system information or displays was selected by 84%, highlighting the importance of interpreting plant information sources (e.g., process indicators, dashboards, HMIs) to support accurate operational judgment. Finally, anticipating or predicting machine or system behavior was selected by 58%, reflecting a strong emphasis on forward-looking reasoning needed to prevent disruptions and support proactive decision-making.

The open-ended responses provided richer descriptions of the SA competencies industry expects newly graduated engineers to bring into the workplace. As shown in Table 1, thematic analysis yielded four themes: Process Understanding and Familiarity, Communication, Trend Analysis and Data Interpretation, and Attention and Anomaly Recognition. These themes reflect the types of SA skills that respondents considered most important for new engineers entering manufacturing environments.

Responses under *Process Understanding and Familiarity* emphasized hands-on engagement and end-to-end knowledge of the production process, including familiarity with equipment behavior and plant interfaces. Participants stressed that early-career engineers should be trained to understand the process “like operators,” and should develop the ability to assess processes holistically rather than in isolated steps. This finding suggests that SA in manufacturing depends heavily on contextual process knowledge. New engineers need to understand not only individual machines or tasks, but also how equipment, people, information, and process steps interact within the broader production system.

The theme of *Attention and Anomaly Recognition* reflected the need for engineers to remain observant, notice when something is missing or out of sequence, and detect subtle changes that may signal emerging problems. Examples include paying attention to machine sound, output quality, safety procedures, and hidden issues on the shop floor. This theme reflects the perceptual foundation of SA: engineers must first notice relevant cues before they can interpret or respond to them. In manufacturing settings, missing early warning signs can lead to quality defects, equipment damage, or unsafe conditions. Therefore, the ability to detect anomalies and maintain attention is a critical competency for new engineers.

Communication emerged as a workplace-enabling competency, with participants emphasizing open communication with shop-floor personnel, receptiveness to frontline information, and willingness to ask clarifying questions rather than making assumptions.

Finally, *Trend Analysis and Data Interpretation* captured the importance of moving beyond single-defect thinking toward identifying patterns over time, understanding trend data, and recognizing when missing data limits decision quality. Respondents noted that new engineers should understand trend data, recognize missing data, and consider upstream and downstream process impacts. Although this theme appeared less often than the others, it is highly relevant to modern manufacturing environments where engineers increasingly rely on data, dashboards, alarms, and digital process information. Trend analysis supports the ability to move beyond immediate observations and anticipate future system behavior. This is especially important for preventing failures, identifying quality risks, and supporting continuous improvement.

As revealed in Table 2, when interpreted through Endsley's three level model, the findings show that respondents described skills across all three levels of SA. Level 1: Perception is reflected in Attention and Anomaly Recognition, where engineers must detect relevant cues such as abnormal sounds, quality changes, unsafe conditions, or unusual system behavior. Level 2: Comprehension is reflected in Process Understanding and Familiarity and Communication, because engineers must understand what observed cues mean in relation to equipment, operators, process flow, and production goals. Level 3: Projection is reflected in Trend Analysis and Data Interpretation, as well as system anticipation, where engineers use current information to predict possible failures, disruptions, or downstream consequences.

Overall, the structured and open-ended findings converge to show that industry expects SA competencies spanning real-time attentional monitoring, system comprehension, and predictive reasoning, grounded in deep process familiarity and strengthened through communication and data-informed trend interpretation. The emphasis on anomaly recognition suggests that attentional discipline and real-time monitoring are critical for preventing safety incidents and production disruptions. Engineers are expected to interpret complex information streams, integrate process knowledge across departments, and anticipate cascading consequences before failures occur. This shift from reactive troubleshooting to proactive system management highlights SA as a strategic capability that enhances safety, quality, and efficiency simultaneously. Thematic findings further broaden this implication. Process understanding and familiarity indicates the need for engineers to develop mental models of entire production systems rather than isolated components. Trend analysis and data interpretation reflect the growing importance of pattern recognition in digitalized manufacturing environments.

The findings suggest the need for SA to be integrated into engineering education curricula as a measurable non-technical skill. Ultimately, embedding SA development within engineering education may represent a strategic investment in preparing engineers who can operate safely, adapt quickly, and contribute to resilient manufacturing systems in increasingly complex industrial landscapes. Manufacturing-related coursework could also include plant simulations, case studies of process failures, HMI-based exercises, operator-centered design activities, and structured reflection on shop-floor observations. Similarly, employers could strengthen onboarding by pairing new engineers with experienced operators, using walkthroughs of production systems, and creating scenario-based exercises focused on detecting and interpreting abnormal conditions.

Table 1: Thematic Frequency Analysis

Theme	Frequency	Percent of responses
Process Understanding and Familiarity	8	50.0%
Communication	6	37.5%
Trend Analysis and Data Interpretation	5	31.3%
Attention and Anomaly Recognition	5	31.3%

Table 2: Mapping to the Endsley's Three Level Model

Endsley level	Meaning	Related theme(s)	Frequency	Percent of responses
Level 1: Perception	Detecting relevant cues in the environment.	Attention and Anomaly Recognition; hands-on/floor awareness	6	37.5%
Level 2: Comprehension	Understanding the meaning of cues and system conditions.	Process Understanding and Familiarity; Communication; Trend Analysis and Data Interpretation	13	81.3%
Level 3: Projection	Anticipating future states, consequences, or failures.	Trend Analysis and Data Interpretation; systems anticipation; anomaly/failure detection	5	31.3%

Conclusion

This study presents an effort to examine SA as a critical non-technical competency within manufacturing practice, and identify how these practitioner insights can inform engineering education focusing on training approaches, observed early-career skill gaps, and industry-prioritized competencies for workforce readiness. The results indicate that training for SA skill in manufacturing is predominantly rely on mentorship and on-the-job learning. While respondents reported high perceived effectiveness and confidence in their own SA abilities, the absence of

structured training frameworks suggests potential variability in how consistently these competencies are developed across organizations. This highlights the need for more systematic approaches to cultivating SA within industry settings. The prominent skill gaps among newly graduated engineers were concentrated in interpreting system behavior and anticipating future outcomes. At the same time, despite professionals emphasized anomaly recognition, system understanding, and predictive reasoning as essential for daily operations and future manufacturing contexts, result shows that SA in engineering contexts is not purely an NTS but a hybrid competency involving both cognitive skills and specific technical expertise. Embedding SA development within both workplace training and engineering curricula may enhance early-career readiness and better align educational preparation with evolving industry demands. While SA has been extensively examined in aviation and healthcare, its structured investigation within manufacturing and engineering workforce preparation remains limited. Firstly, this study provides empirical validation that SA is actively recognized by industry professionals as essential for operational performance and future workforce readiness. Secondly, the findings identify a clear developmental gap between industry expectations and early-career capabilities. This insight has practical implications for organizations seeking to enhance training programs and reduce the time required for new engineers to achieve operational competence. Thirdly, the study offers direct implications for engineering education by supporting structured SA development into curricula through experiential and scenario-driven learning approaches. This alignment can improve workforce readiness and reduce the disconnect between academic preparation and industrial demands. Finally, in an era of increasing automation, digitalization, and complex human–machine systems, strengthening SA contributes to manufacturing resilience, safety, and proactive decision-making. Therefore, this study not only contributes theoretically to the literature on NTS but also provides actionable insights for educators, industry leaders, and workforce development initiatives. As this study evolves, the goal is not only to articulate the importance of SA in manufacturing but also to build an evidence-based framework for embedding SA competency into engineering education. This ongoing process will contribute to bridging the education–practice divide and supporting the preparation of a workforce equipped to operate, manage, and innovate within increasingly complex sociotechnical production systems.

References

- [1] E. Flores Arriaga, “OPERATOR 4.0: A HUMAN PERSPECTIVE OF INDUSTRY 4.0,” 2022.
- [2] M. Golovianko, V. Terziyan, V. Branytskyi, and D. Malyk, “Industry 4.0 vs. Industry 5.0: Co-existence, Transition, or a Hybrid,” in *Procedia Computer Science*, Elsevier B.V., 2022, pp. 102–113. doi: 10.1016/j.procs.2022.12.206.
- [3] U. Körner, K. Müller-Thur, T. Lunau, N. Dragano, P. Angerer, and A. Buchner, “Perceived stress in human–machine interaction in modern manufacturing environments—Results of a qualitative interview study,” *Stress and Health*, vol. 35, no. 2, pp. 187–199, Apr. 2019, doi: 10.1002/smi.2853.
- [4] M. L. Nicora, R. Ambrosetti, G. J. Wiens, and I. Fassi, “Human-Robot Collaboration in Smart Manufacturing: Robot Reactive Behavior Intelligence,” *JOURNAL OF MANUFACTURING SCIENCE AND ENGINEERING-TRANSACTIONS OF THE ASME*, vol. 143, no. 3, 2021, doi: 10.1115/1.4048950.

- [5] S. H. Khan and A. H. I. Mourad, "Integrating Industry 4.0 in engineering education: implementation patterns, pedagogical strategies, and industry alignment," 2025, *Taylor and Francis Ltd.* doi: 10.1080/2331186X.2025.2588010.
- [6] Schulz Jeff, "Technical vs. Soft Skills: What Matters More in an Upskilling Program?," Aug. 13, 2025.
- [7] Smith Wes, "Bridging the Workforce Gap: The Need for Soft and Technical Skills in Manufacturing," *Manufacturing Skills Institute (MSI)*, Feb. 03, 2025.
- [8] R. Flin, P. O'Connor, and M. Crichton, *Safety at the Sharp End: A Guide to Non-Technical Skills*. 2017. doi: 10.1201/9781315607467.
- [9] M. Barger and R. Gilbert, "Future of Work Skills Integration with Florida Manufacturers' Technician Skill Needs," *JATE*, vol. 2023, p. 1, 2023, doi: 10.5281/zenodo.7776408.
- [10] M. A. Hazrat, N. M. S. Hassan, A. A. Chowdhury, M. G. Rasul, and B. A. Taylor, "Developing a Skilled Workforce for Future Industry Demand: The Potential of Digital Twin-Based Teaching and Learning Practices in Engineering Education," *Sustainability*, vol. 15, no. 23, p. 16433, Nov. 2023, doi: 10.3390/su152316433.
- [11] J. D. Azofeifa, V. Rueda-Castro, C. Camacho-Zuñiga, G. M. Chans, J. Membrillo-Hernández, and P. Caratozzolo, "Future skills for Industry 4.0 integration and innovative learning for continuing engineering education," *Front. Educ. (Lausanne)*, vol. 9, 2024, doi: 10.3389/feduc.2024.1412018.
- [12] A. Harper, N. Mustafee, and M. Pitt, "Increasing situation awareness in healthcare through real-time simulation," *JOURNAL OF THE OPERATIONAL RESEARCH SOCIETY*, vol. 74, no. 11, pp. 2339–2349, 2023, doi: 10.1080/01605682.2022.2147030.
- [13] S. Feller, L. Feller, A. Bhayat, G. Feller, R. A. G. Khammissa, and Z. I. Vally, "Situational Awareness in the Context of Clinical Practice," Dec. 01, 2023, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/healthcare11233098.
- [14] K. W. Williams, "Impact of aviation highway-in-the-sky displays on pilot situation awareness," *Hum. Factors*, vol. 44, no. 1, pp. 18–27, 2002, doi: 10.1518/0018720024494801.
- [15] D. B. Kaber, J. M. Riley, M. R. Endsley, M. Sheik-Nainar, T. Zhang, and D. R. Lampton, "Measuring situation awareness in virtual environment-based training," *Military Psychology*, vol. 25, no. 4, pp. 330–344, Jul. 2013, doi: 10.1037/h0095998.
- [16] V. R. Patel, C. L. Bethel, J. E. Swan, D. Carruth, T. J. Jankun-Kelly, and J. M. Keith, "Using dynamic task allocation to evaluate driving performance, situation awareness, and cognitive load at different levels of partial autonomy," 2023.
- [17] M. R. Endsley, "Situation awareness in dynamic human decision-making: Theory and measurement," 1990.
- [18] M. R. Endsley, "Toward a Theory of Situation Awareness in Dynamic Systems," 1995.

- [19] M. R. Endsley, "Situation Awareness and Human Error: Designing to Support Human Performance," 1999. [Online]. Available: <https://www.researchgate.net/publication/252848339>
- [20] E. J. Isoghie and J. J. Saleem, "Drivers and Barriers to High Situation Awareness in Manufacturing: A Literature Review," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 69, no. 1, pp. 647–650, Sep. 2025, doi: 10.1177/10711813251364789.
- [21] M. Lall, H. Torvatn, and E. A. Seim, "Towards industry 4.0: Increased need for situational awareness on the shop floor," in *IFIP Advances in Information and Communication Technology*, Springer New York LLC, 2017, pp. 322–329. doi: 10.1007/978-3-319-66923-6_38.
- [22] S. J. Anbro *et al.*, "Using Virtual Simulations to Assess Situational Awareness and Communication in Medical and Nursing Education: A Technical Feasibility Study," *J. Organ. Behav. Manage.*, vol. 40, no. 1–2, pp. 129–139, Apr. 2020, doi: 10.1080/01608061.2020.1746474.
- [23] D. D. Heikoop, J. C. F. de Winter, B. van Arem, and N. A. Stanton, "Effects of mental demands on situation awareness during platooning: A driving simulator study," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 58, pp. 193–209, Oct. 2018, doi: 10.1016/j.trf.2018.04.015.
- [24] R. M. S. Clifford, T. McKenzie, S. Lukosch, R. W. Lindeman, and S. Hoermann, "The Effects of Multi-sensory Aerial Firefighting Training in Virtual Reality on Situational Awareness, Workload, and Presence," in *Proceedings - 2020 IEEE Conference on Virtual Reality and 3D User Interfaces, VRW 2020*, Institute of Electrical and Electronics Engineers Inc., Mar. 2020, pp. 93–100. doi: 10.1109/VRW50115.2020.00023.
- [25] N. Groner, "A situation awareness requirements analysis for the use of elevators during fire emergencies," 2009. [Online]. Available: <https://www.researchgate.net/publication/292112336>
- [26] N. Marquardt, "Situation awareness, human error, and organizational learning in sociotechnical systems," *HUMAN FACTORS AND ERGONOMICS IN MANUFACTURING & SERVICE INDUSTRIES*, vol. 29, no. 4, pp. 327–339, 2019, doi: 10.1002/hfm.20790.
- [27] Y. Chi, J. Nie, L. Zhong, Y. Wang, and D. Delahaye, "A Review of Situational Awareness in Air Traffic Control," *IEEE Access*, vol. 11, pp. 134040–134057, 2023, doi: 10.1109/ACCESS.2023.3336415.
- [28] C. Y. Arias-Portela, J. Mora-Vargas, and M. Caro, "Situational Awareness Assessment of Drivers Boosted by Eye-Tracking Metrics: A Literature Review," Feb. 01, 2024, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/app14041611.
- [29] M. D. Matthews and S. A. Beal, "Assessing Situation Awareness in Field Training Exercises," 2002.

- [30] L. R. Enders *et al.*, “Evidence of elevated situational awareness for active duty soldiers during navigation of a virtual environment,” *PLoS One*, vol. 19, no. 5 May, May 2024, doi: 10.1371/journal.pone.0298867.
- [31] A. A. Alfuraydi and M. Al-Moteri, “Real-time assessment of triage nurse situational awareness (SA) using the situation awareness global assessment technique (SAGAT),” *PLoS One*, vol. 20, no. 2 February, Feb. 2025, doi: 10.1371/journal.pone.0318555.
- [32] J. J. Chen, A. Gompers, A. Evenson, B. C. James, and C. Royce, “Surgical Adaptation of the Situation Awareness Rating Technique (S-SART): Assessing Situational Awareness Among Medical Students,” *J. Surg. Educ.*, vol. 80, no. 2, pp. 216–227, Feb. 2023, doi: 10.1016/j.jsurg.2022.09.015.
- [33] K. Jonsson, C. Brulin, M. Härgestam, M. Lindkvist, and M. Hultin, “Do team and task performance improve after training situation awareness? A randomized controlled study of interprofessional intensive care teams,” *Scand. J. Trauma Resusc. Emerg. Med.*, vol. 29, no. 1, Dec. 2021, doi: 10.1186/s13049-021-00878-2.
- [34] M. S. Bracq, E. Michinov, M. Le Duff, B. Arnaldi, V. Gouranton, and P. Jannin, “Training situational awareness for scrub nurses: Error recognition in a virtual operating room,” *Nurse Educ. Pract.*, vol. 53, p. 103056, May 2021, doi: 10.1016/j.nepr.2021.103056.
- [35] B. Green, D. Parry, R. S. Oepfen, S. Plint, T. Dale, and P. A. Brennan, “Situational awareness – what it means for clinicians, its recognition and importance in patient safety,” Sep. 01, 2017, *Blackwell Publishing Ltd.* doi: 10.1111/odi.12547.
- [36] H. Kim, J. Hong, and S. Lee, “Investigating impact of situation awareness-based displays of semi-autonomous driving in urgent situations,” *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 105, pp. 454–472, Aug. 2024, doi: 10.1016/j.trf.2024.07.018.
- [37] P. Illankoon, Y. Manathunge, P. Tretten, J. Abeysekara, and S. Singh, “Lockout and Tagout in a Manufacturing Setting from a Situation Awareness Perspective,” *SAFETY*, vol. 5, no. 2, 2019, doi: 10.3390/safety5020025.
- [38] Y. Cai and P. L. P. Rau, “Attention Allocation to Projection Level Alleviates Overconfidence in Situation Awareness,” *J. Cogn. Eng. Decis. Mak.*, vol. 18, no. 3, pp. 187–208, Sep. 2024, doi: 10.1177/15553434241254663.
- [39] A. D. Landmark, E. Arica, B. Kløve, F. Kamsvåg, E. A. Seim, and M. Oliveira, “Situation Awareness for Effective Production Control,” pp. 690–698, 2019, doi: 10.1007/978-3-030-30000-5_84i.
- [40] G. M. Wilson, R. T. Stone, and K. M. Schaffhausen, “Analysis of situation awareness-related incidents in the food manufacturing industry,” *International Journal of Industrial and Systems Engineering*, vol. 45, no. 4, pp. 417–431, 2023, doi: 10.1504/IJISE.2023.135772.
- [41] M. Chandanani, A. Laidlaw, and C. Brown, “Extended reality and computer-based simulation for teaching situational awareness in undergraduate health professions education: a scoping

- review,” *Advances in Simulation*, vol. 10, no. 1, Dec. 2025, doi: 10.1186/s41077-025-00343-5.
- [42] C. Brown, M. Chandanani, and A. Laidlaw, “Virtual, augmented and mixed reality simulation for teaching and assessing situational awareness and decision-making in health professions education: a scoping review protocol,” *International Journal of Healthcare Simulation*, Jan. 2024, doi: 10.54531/wnzw3461.
- [43] D. Fukuta and M. Iitsuka, “Nontechnical Skills Training and Patient Safety in Undergraduate Nursing Education: A Systematic Review,” *Teaching and Learning in Nursing*, vol. 13, no. 4, pp. 233–239, Oct. 2018, doi: 10.1016/j.teln.2018.06.004.
- [44] M. R. Endsley, *SA Demons: The Enemies of Situation Awareness. In Designing for Situation Awareness: An Approach to User-Centered Design*. CRC Press, 2016.

Appendix

Industry Survey - Needs for Situation Awareness (SA) Skills in Manufacturing Industry

Introduction

In modern manufacturing environments, the ability to maintain situation awareness (SA) is essential. Manufacturing systems are complex and produce large amounts of data. Workers are required to process large volumes of information from machine interfaces, control systems, and collaborative robots (cobots). The ability to maintain high levels of situation awareness in these contexts influences the quality of decisions, timely detection of anomalies, and ability to respond effectively to dynamic changes in manufacturing environments. Conversely, breakdowns in situation awareness can lead to production delays, errors, safety incidents, and equipment failures. This survey is part of a research project aimed at understanding the context for situation awareness (SA) skills in the manufacturing industry and ultimately developing a framework for situation awareness training for undergraduate engineering students. The survey takes about 15-25 minutes to complete. Your responses will be kept confidential. Participation is voluntary and anonymous. You may skip any question or stop at any time.

Section 1: Respondent Information

1. What is your current job title/role? _____
 - a. Operator
 - b. Engineer
 - c. Supervisor
 - d. Other
2. How many years of experience do you have in manufacturing?
 - a. 0-3 years
 - b. 4-6 years
 - c. 7-9 years
 - d. Over 9 years
3. What is your organization's primary industry?
 - Automotive
 - Aerospace
 - Electronics
 - Food Processing
 - Energy
 - Other _____
4. Number of employees
 - a. 1-50
 - b. 51-200
 - c. 201-500
 - d. 501+
5. Location (City, State)
6. Name and Email address _____
7. What is the **most prevalent level of automation** based on decisions and the degree of human involvement in the work you do? (*Select all that apply*)
 - a.** Machine performs operations without human intervention
 - b.** Human approves machine suggestions before it is executed
 - c.** Machine makes the decision to inform humans on the course of action

- d.* The machine supplies power, information, decisions and control while the human performs a supervisory role
 - e.* Humans perform all functions without machine intervention
8. Where do you do most of your work?
- a. Assembly line
 - b. Control room
 - c. Maintenance zone
 - d. Quality/testing area
 - e. Other: _____

Section 2: Contextual Application of SA Skills

Situation awareness (SA) is the ability to notice what is happening, understand what it means, and predict what may happen next.

9. Which **situation awareness-related errors happen most often** in your work? *(Select all that apply)*
- a.* Information about the system or process is not available
 - b.* Wrong understanding of the process status
 - c.* Information difficult to notice, perceive or discriminate
 - d.* Overconfidence
 - e.* Not understanding how the system or process works
 - f.* Seeing or reading the data the wrong way
 - g.* Failure to monitor or observe data
 - h.* Use of wrong information
 - i.* Other
10. What **support** helps improve **situation awareness** in your workplace? *(Select all that apply)*
- a. Specialized training
 - b. Real-time screen display
 - c. Clear and easy-to-follow procedures
 - d. Better team communication practices
 - e. Other _____

11. Describe a real-world scenario where **a loss or gain in situation awareness** significantly affected operations, work or safety (open-ended question)
12. Describe a scenario in which **prior experience** significantly **enhances your situation awareness** (open-ended question)

Section 3: Training and Learning

13. What methods were used in your **situation awareness (SA) training**? (*Select all that apply*).

- On-the-job mentorship
- Simulated scenarios
- Team walkthrough
- None
- Other, please specify _____

14. How effective was the training in improving your situation awareness (SA) skills?

- Very effective
- Somewhat effective
- Neither effective nor ineffective
- Somewhat ineffective
- Very ineffective

15. What **Situation Awareness (SA) skills** do **new engineers** typically struggle with when working in your team? (*Select all that apply*)

- Identifying what cues to pay attention to
- Detecting what is happening in the system
- Interpreting system behavior for process safety or improvement
- Anticipating changes or problems
- Other _____

16. Which **Situation Awareness (SA) skills** are most essential in your **daily work** or for **future manufacturing workers**? (*Select all that apply*)

- Perceiving or detecting anomalies or unexpected changes
- Understanding system information or displays
- Anticipating or predicting machine or system behavior
- Other

17. Describe a scenario or context where situation awareness skills help you in improving your process or ensure safe operation. (open-ended question)

18. Quantitative Items (Likert Scale: 1 = Strongly Disagree to 5 = Strongly Agree)

- I feel confident in my situation awareness skills.

- I anticipated the need for situation awareness skills.
19. What **situation awareness skills** would you recommend that **newly graduated engineers** bring with them to the manufacturing workplace? (*open-ended question*)

Section 4: Perception level of Situation Awareness

(Detecting key elements in the manufacturing environment, for example, noticing that a warning light is flashing, a robot arm has paused, or a part is misaligned on the conveyor.)

20. What types of tools help you perceive critical information in your work environment (select *all that apply*) (*SA Enablers*)?
- Visual signs
 - Clear displays
 - Visual standards (e.g., color codes)
 - Audible alarms
 - Sensor
 - Other _____
21. What challenges make it difficult to perceive important information (select *all that apply*)?
- Focusing on one thing (Attention tunneling)
 - System complexity
 - Automation (Out-of the-loop syndrome)
 - Focusing on wrong cues
 - Workload, Anxiety, Fatigue and other stressors
 - Too many information available
 - Other _____
22. How often does poor perception impact your ability to detect safety hazards or make decisions in real time?
- Never
 - Rarely
 - Sometimes
 - Often
 - Very often

Section 5: Comprehension level of Situation Awareness

(Understanding what the system is doing, for instance, knowing why a light is flashing, why a robot arm stopped, or what a safety alarm means.)

23. What challenges make it difficult to comprehend information (select all that apply)?

- Rapidly changing information
- Poor understanding of how the system works (Errant mental model)
- Needing to remember too much information (Requisite memory trap)
- Workload, Anxiety, Fatigue and other stressors
- System complexity
- Other__

24. When interpreting information, what helps you understand it accurately? (**Select all that apply**)

- Prior experience
- Data Visualization
- Digital dashboards/Display
- Training/briefings
- Real-time decision aids
- Scenario-based simulations
- Other _

Section 6: Projection level of Situation Awareness

(Thinking ahead about what may happen next based on what is happening now. For example, predicting a machine stop if a problem is not fixed, a delay in production, or safety risks if an issue continues.)

25. What hinders your ability to anticipate problems or hazards in your work? (**Select all that apply**)

- Time pressure
- System complexity
- Missing information
- Task switching
- Flawed understanding of the system (Errant or poor mental model)
- Other _____

26. What helps you better anticipate or predict changes, errors, or flaws in manufacturing processes or systems? (**Select all that apply**)

- Pattern recognition
- Accurate understanding of the task/process
- Prior experience
- Early warning signs
- Other _____

27. Can you share a scenario where you anticipated a problem before it happened? What helped you do that? (open-ended questions)

Section 7: Cognitive Factors Affecting Situation Awareness.

28. Rate how accurately each statement describes your experience while carrying out your **manufacturing tasks**. (Strongly Disagree -1 to Strongly Agree -5)

- a. I often have to keep multiple steps or tasks in mind while performing my work.
- b. I sometimes forget steps or actions when I am interrupted.
- c. I am required to mentally track information across multiple displays or tools.
- d. I find it challenging to switch attention between tasks without losing focus.
- e. I have developed mental strategies to stay focused during repetitive tasks.
- f. Information overload sometimes makes it difficult to stay aware of the situation.
- g. The tools I use help reduce the mental effort required to keep track of tasks.
- h. My mental understanding matches what actually happens during production.
- i. I have a clear mental picture of how the manufacturing system operates.

Situation Awareness in Human-Robot Interaction (HRI)

This section asks about your experiences working with robots and automated systems in manufacturing. These could include collaborative robots (cobots), robotic arms, automated material handlers, or smart machines. Your responses will help us understand how **situation awareness** is developed and challenged in these settings.

29. Do you work with robots?

- Yes
- No

30. What type of robots do you work with? (*Select all that apply*)

- Collaborative robots (cobots)
- Industrial arms
- Mobile robots (Automated Guided Vehicles/Autonomous Mobile Robots)
- None
- Other

31. **A Perception-Level Situation Awareness in Human-Robot Interaction (Likert Scale: Strongly Disagree-1 to Strongly Agree- 5)**

- a. I can quickly tell what task the robot is performing at any moment.
- b. The robot provides clear signals when it's about to move or change actions.
- c. I can detect when the robot is not working as expected.
- d. I can track where the robot is in its task sequence.

32. **Comprehension-Level Situation Awareness in Human-Robot Interaction (Likert Scale: Strongly Disagree-1 to Strongly Agree- 5)**

- a. I understand how the robot's actions relate to the larger manufacturing process.
- b. I know why the robot behaves the way it does during my tasks.
- c. I can tell when a problem is caused by the robot, human input, or another system.
- d. I understand how my actions influence the robot's behavior.

e. I can interpret robot signals, displays, or alarms during collaboration.

33. Projection-Level Situation Awareness in Human-Robot Interaction (Likert Scale: Strongly Disagree-1 to Strongly Agree- 5)

- a. I can anticipate the robot's next move during joint tasks.
- b. I feel confident predicting how the robot will respond to unexpected events (e.g., missing parts, blocked paths).
- c. I can plan my actions based on what the robot is about to do.
- d. I feel confident that I know what will happen if I interrupt or override the robot.
- e. I can foresee delays or risks caused by poor timing between me and the robot.

Appendix 2: Codebook

Code	Theme	Definition	Included indicators / examples	Primary Endsley level
T1	Process Understanding and Familiarity	Understanding the production process, equipment, HMIs, workflows, operator practices, and how system components interact.	Process assessment; hands-on approach; HMI/process understanding; operator-level equipment training; process improvement; systems anticipation	Level 2: Comprehension
T2	Communication	Using questions, listening, and operator interaction to build shared understanding and avoid assumptions.	Open communication; asking questions; 5 Whys; Ishikawa; operator-centered awareness	Level 2: Comprehension
T3	Trend Analysis and Data Interpretation	Using data, patterns, missing information, and system relationships to support decisions and anticipate outcomes.	Trend data; missing data; impact mapping; systems anticipation; process analysis	Level 2: Comprehension; Level 3: Projection
T4	Attention and Anomaly Recognition	Maintaining attention, observing the shop floor, recognizing abnormal conditions, and detecting early warning signs.	Safety attentiveness; avoiding distractions; environmental scanning; abnormal sound/output; hidden-factory detection	Level 1: Perception