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Attention And Reasoning From Experts In Smart Manufacturing With Digital Twin Implementations

Ansari Amir Babujan[1],Yusuf Shahzad[2],Ritik Kumar[3]
[1,2,3]Students, School of Management, Noida Institute of Engineering and Technology Greater Noida, India
aamirking2007@gmail.com[1], yshahzad270@gmail.com[2], ritikpol021@gmail.com[3]

ABSTRACT: *When it is well known that expert attention is a way to separate each attention head into its own expert in a Mixture-of-Experts design, we understand that, inside the implementation of the digital twin, we need to examine how expert attention and reasoning engagement can enable operative Human-Machine Partnership in Industry 6.0 environments in the near future. We focused on analysing how user-centric design elements moderate these relationships, based on data from the most successful factory projects. A multiple-case study approach was used to examine data from Siemens, GE, and Bosch, three major industry players, which were publicly available. The study used a structured qualitative review of performance measures, system designs, and reported results from Digital Twin applications in the Manufacturing sectors. Three key patterns appear throughout the study. First, expert attention requires intelligent information filtering rather than increased data availability, as the latter would only take up space. Second, the reasoning involvement depends on AI answers that are clear, build trust, and can allow control. Third, user-centric design increases the cognitive effects when matched to users' expertise levels. All three companies in the study demonstrated double-digit improvements in efficiency, accuracy, and response times over cognitive-focused Digital Twin designs. Throughout the study, we found that companies should invest in explainable AI, match interface complexity to user expertise, and design for learning rather than performance to better implement Digital Twins. They should also prioritise attention support through intelligent filtering, reasoning support through transparent clarifications, and user-centric revision. This study advances Industry 6.0 from a conceptual vision to a practical reality, providing the first systematic analysis of the mechanisms of cognitive engagement in operational Digital Twin systems and offering a framework for experts and a basis for future research.*

KEYWORDS: *Industry 6.0; Digital Twin; Human-Machine Collaboration; Cognitive Engagement; Expert Attention; Reasoning; User-Centric Design; Case Study; Siemens; GE; Bosch.*

1. INTRODUCTION

The manufacturing sector is changing faster than before. Historically, factories used simple machines; then came computers and automation. But now we are part of Industry 4.0, in which machines are connected to the internet and share data, which is helping factories operate more efficiently and accurately and making manufacturing safer. But as the internet and data connectivity advance, enabling multiple devices to connect at once, the industry 4.0 advancement comes with a problem: it focuses too much on machines and not enough on people. Nowadays, workers are left to watch machines operate, and when problems arise, they often do not know what to do, creating a gap between humans and technology. As we entered Industry 5.0 in 2025, the sector sought to address this by bringing humans back to the centre. The idea is that humans and machines should work together rather than replace each other, giving rise to the concept of Human-Machine Collaboration. As we will in the future move to Industry 6.0, we need the next step to be more focused on, so that humans and machines share thinking work. So the machines do not just follow orders; they can help humans think better, and this needs a new tool, a Cerebral Digital Twin. As a Digital Twin is a copy of a real machine or process on a computer or we can say it is the replica of the real life object in the virtual world and it can be an exact replica if the technology is advanced enough which can shows what is happening in real time which later can be used for the removing the hurdles of the manufacturing before they are occurring in the real world. But we have used the twin technology in the real life companies in the industry 5.0 its is not just the part of the research only we are using it in the real world now we need to more focus on a twin technology which allows the combination of the this coordinatization more than just being a replica we will give this replica a mind so we can say a Cerebral Digital Twin goes further as it can also understands how a human worker thinks so it can helps the worker focus on the right things at right time and allow then to think through problems more effectively. This is important because factory work is becoming more demanding and dangerous as we experiment with more products and expand into more categories. Now this industry demands workers to watch many things at once, they must make quick decisions, and they must work with smart machines that have their own ideas and new settings with each passing day. Which is leading to a Cognitive Gap. Here, if the workers are not quicker, the information gets lost, leading to decisions being delayed and mistakes happening. In this study, we examine how to close this gap. To conduct the study, we used three companies that are leaders in this field of using digital twin technology in the manufacturing sector: Siemens, GE, and Bosch. These companies have built real Digital Twin systems, which lead to the data which can show what works and what does not in the real-world implementation. We use their publicly available information and reports to understand how expert attention and reasoning enable Human-Machine Collaboration to succeed, or is this necessary, and can it work? Because the main problem is the Cognitive Gap in Human-Machine Collaboration. Through the examination, we found that this gap has three parts. First, there is Information Asynchronism, which leads to the disconnection and indicates that a machine can display excessive or incorrect data, which can lead to the worker being unable to find what matters. Second, there is Reasoning Misalignment, such as a machine thinks in numbers and patterns, and a human thinks in context and experience, and they do not speak the same language. So, the worker does not trust the machine, and if we give the cognitive understanding to the machine, the machine does not understand the worker. Third, there is Coordination Failure, as unless there’s a proper schedule and instruction manual, the worker and machine do not know who should do what and they step on each other's work which can lead to the overwork for a worker and for a machine or also can lead to the problems in the machine Or they both wait for the other to act like in normal days in most cases a worker has to come and start the machine and has the all control over so we can say these problems hurt performance which can leads to the decisions are slower and errors are more common and uncommon in lots of cases and which leads to the workers get frustrated and companies lose money. Current Digital Twin systems mainly replicate the physical world objects and only show the virtual structure of the object, but they ignore what the human is thinking. This is the gap we must fill. This study asks two questions.

RQ1: How can expert attention and reasoning engagement help Human-Machine Collaboration in real-world Digital Twin implementations in the manufacturing sector?

RQ2: How can user-centric design elements like intuitive interfaces and dynamic feedback can improve the link between cerebral engagement and performance?

As we compare cases and suggest a framework that others can test in the future, these questions will help us focus on cognitive factors rather than technical trending ones, such as cybersecurity or data architecture.

2. LITERATURE REVIEW

This review employs a Systematic Literature Review with additional components using the PRISMA 2020 guidelines. We used the Web of Science, Scopus, IEEE Xplore, and ScienceDirect. We used keywords such as "Industry 4.0," "Industry 5.0," "Industry 6.0," "Digital Twin," "Human-Machine Collaboration," and "cognitive engagement." We found 2,847 total no of papers later we removed duplicates then screened titles and abstracts of the remained papers through this study we read 78 full papers but behalf of the study we selected only 56 for qualitative review as we were more focused on papers from 2024 to 2026 to capture recent developments and throughout the studies we founded the industry 4.0 started in Germany in 2011 and considered to be ended in the 2025 in the more studies.

Table 1: Evolution of Industrial Paradigms — Key Characteristics

Feature	**Industry 4.0**	**Industry 5.0**	**Industry 6.0**
Time Period	2011–2020	2021–2024	2025–Future
Core Focus	Automation, Efficiency	Human-Centricity, Sustainability	Symbiotic Intelligence
Key Technologies	IoT, Big Data, Cloud, AI	Cobots, Bio-Inspired Systems, Green Tech	Cerebral Digital Twins, Brain-Computer Interfaces, Generative AI
Human Role	Supervisor of Machines	Collaborative Partner	Cognitive Partner in Symbiosis

Primary Question	How can machines replace humans?	How can machines help humans?	How can humans and machines think as one?
Value Driver	Economic Optimization	Human Flourishing + Profit	Human Flourishing as Ultimate Goal
Sustainability	Resource Efficiency	Circular Economy, Carbon Neutral	Carbon Negative, Regenerative Systems
Resilience Approach	Technical Redundancy	Organizational Adaptability	Ecosystem Self-Healing
Cognitive Demand	Monitoring, Basic Troubleshooting	Collaborative Problem-Solving	Deep Reasoning, Creative Synthesis

With the help of multiple resource studies, we define the type of digital twin technology with its core functions and further explore its applications in various fields and how they can provide enhancements in the upcoming industry revolution and can add value to the existing industry 5.0.

Table 2: Types of Digital Twins — Functions and Applications

Type	**Definition**	**Primary Function**	**Data Sources**	**Industry 6.0 Enhancement**
Product Digital Twin	Virtual replica of a single asset or component	Predictive maintenance, Performance monitoring	Sensors on equipment, Operational logs	Real-time cognitive monitoring with attention guidance
Production Digital Twin	Virtual model of manufacturing processes	Process optimisation, Layout planning	Production line sensors, Workflow data	Collaborative planning with reasoning support tools
Performance Digital Twin	Integration of operational and business metrics	Strategic decision-making, Resource allocation	ERP systems, Business intelligence data	Cognitive augmentation for complex trade-off analysis
Cerebral Digital Twin	Real-time model of human cognitive states and physical systems	Attention management, Reasoning support, Cognitive load optimisation	Physiological sensors, Eye-tracking, Interaction patterns, Behavioural data	Symbiotic cognitive partnership between human and machine

For Industry 6.0, we need a fourth type of digital twin, as it's the requirement of the ongoing changes, as the Cerebral Digital Twin will be able to help us to process the future with more efficiency. This type of virtual copy not only works with a machine but also with the human mind, which tracks attention and later supports reasoning by adapting to the worker's cognitive state. Human-Machine Collaboration (HMC) refers to the integration of human and machine capabilities to work together as partners with the machine, or we can say the imagination of the human and machine becoming one to perform one task. This is different from automation, as in HMC, they complement each other because we humans are good at context, creativity, and ethical judgment, but our machines excel at speed, precision, and continuous monitoring and together, we as the HMC can do more than either alone. But collaboration is hard, as humans and machines must understand each other to coordinate their actions to work on shared goals, but when this fails, we get the Cognitive Gap, which needs to be solved.

2.5 The Cognitive Gap

At the beginning of the study, the Cognitive Gap has to be separated into three parts. First was the Information asynchrony, which can lead to the lack of effective data flow between humans and machines. The machine may show too much or too little, but the human can miss signals or be overwhelmed by noise, leading to errors.

Table 3: The Cognitive Gap — Manifestations, Causes, and Solutions

Manifestation	Description	Root Causes	Negative Consequences	Design Solution
Information Asynchrony	Misalignment between data presentation and human attention capacity	Information overload; Poor signal-to-noise ratio; Inappropriate pacing	Missed critical indicators; Delayed responses; Vigilance decrements	Intuitive interface with progressive disclosure; Attention-guiding visualisations
Reasoning Misalignment	A disconnect between algorithmic logic and human cognitive patterns	Algorithmic opacity; Counterintuitive outputs; Lack of explanation	Eroded trust; Poor error detection; Failed collaborative problem-solving	Transparent AI with explainable recommendations; Reasoning scaffolding tools
Coordination Failure	Unclear allocation of authority and responsibility between humans and machines	Ambiguous role definitions; Poor handoff protocols; Conflicting assumptions	Missed handoffs; Duplicated efforts; Dangerous autonomy gaps	Clear role definition protocols; Dynamic feedback on system state and intent

In Digital Twin environments, attention is dangerous because the system produces large amounts of data while processing big data; only an expert's attention can identify the important parts. As reasoning engagement involves deep thinking, it is not enough to see the data; the worker needs to apply their knowledge to interpret it and decide what to do. This takes mental effort, and good Digital Twin systems support this effort, but bad systems block it and as the centric design puts the worker first. Only two elements matter most

- Intuitive Interface Design means the system is easy to understand for each category of workers. Buttons are where users expect. Actions have clear results. Learning is fast. Errors are few.
- Dynamic Feedback means the system responds immediately. It tells users what is happening. It explains its reasoning. It adapts to the user's needs.

Based on this review, we propose a framework where expert Attention leads to Reasoning Engagement. Reasoning Engagement leads to better Decision Accuracy and Process Efficiency. User-centric Design moderates these relationships, strengthening them. Our framework guides our case study analysis, for which we seek evidence of these links in the implementations of Siemens, GE, and Bosch.

3. METHODOLOGY

3.1 Research Design

Utilising a multiple-case study method will allow the researchers to examine digital twin implementations across companies that are leaders in this field. The sample cases studied for this project are Siemens, GE, and Bosch; all three companies provide publicly accessible information about their digital twin implementations. The authors will analyse the respective corporate reports and other materials for each of the three companies to aid understanding of cognitive engagement in the workplace. The authors believe that a case study approach is the best way to do this, as it enables a thorough investigation of those companies' digital twin systems in real-world settings. In addition, the authors will primarily use qualitative methods to analyse all three companies, rather than statistical analysis. Overall, the goal of the qualitative analysis will be to identify themes and patterns that emerge throughout all three case studies through case study research and comparative analyses of the three companies. Although no individual survey data were collected from any employees, the authors will be relying solely on corporations' publicly available reports regarding their respective systems.

3.2 Case Selection

Siemens is a German company that manufactures equipment and services related to energy and industrial automation; it also has an ATOM platform for managing gas turbines. General Electric (GE) is an American company that operates in aviation, health care, and energy, and it has developed one of the first industrial IoT platforms (Predix) that contains many examples of improved operational performance. Bosch, another German company, is a leading automotive supplier and has developed a variety of industrial IoT solutions; its IoT Suite enables the operation of millions of connected devices. Bosch has also made thousands of tools publicly available and published case studies on the results of implementing them. The three companies are from different industries, so that it will be possible to identify similarities between them, even though they perform completely different functions; therefore, cognitive engagement will have a similar effect regardless of which type of technology is utilised.

3.3 Data Sources

We only used the public data, which includes:

- Company white papers and technical reports
- Academic case studies written about these companies
- Conference presentations by company engineers
- Open-source documentation (especially for Bosch)
- Industry analyst reports

We do not use private information, and all data comes from publicly accessible sources.

Table 4: Case Study Companies — Overview and Data Sources

Company	Headquarters	Primary Industry	Digital Twin Platform	Data Sources Used	Time Period Covered
Siemens AG	Munich, Germany	Energy, Manufacturing	ATOM (Adaptive Technology for Operational Modelling)	Published case studies; Conference presentations; Technical white papers, and fleet operational reports	2019–2024
General Electric (GE)	Boston, USA	Aviation, Healthcare, Energy	Predix Manufacturing Data Cloud	Academic case studies; Industry reports; Public platform documentation; Performance benchmarks	2018–2024

Robert Bosch GmbH	Stuttgart, Germany	Automotive, Industrial IoT	Bosch IoT Suite; Eclipse Ditto open source	Open-source project documentation; Published implementation results; Technical specifications; IoT platform reports	2020–2024

Fig.1. Data Analysis in three steps.

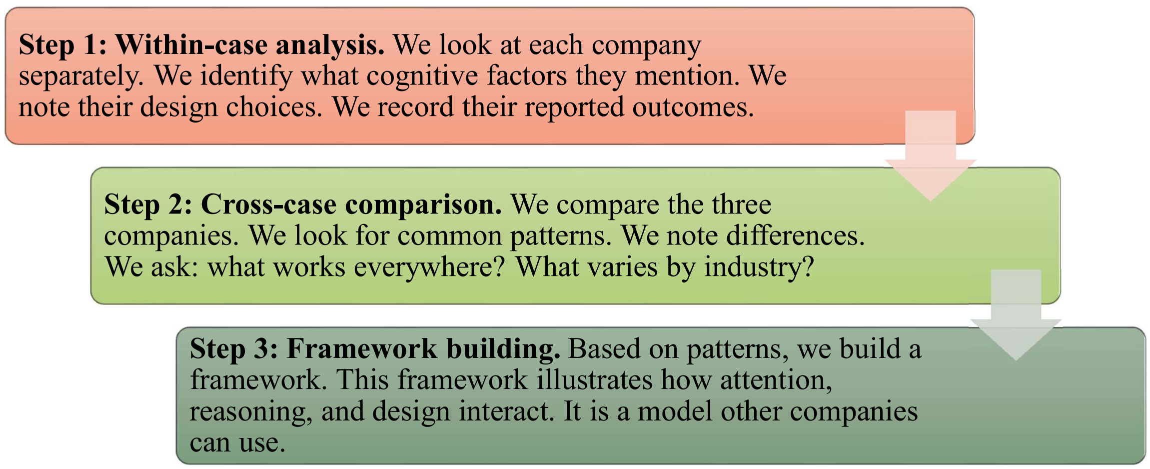
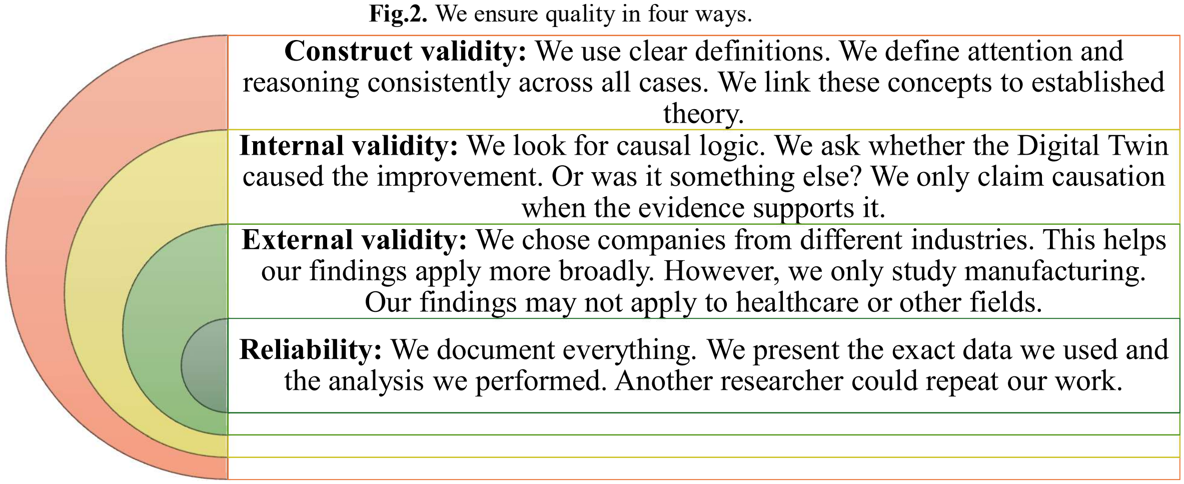


Fig.2. We ensure quality in four ways.



3.6 Limitations

This work has three main limitations. First, the reliance on organisational reports as indicators of employee engagement; these reports are typically written to highlight organisations' strengths and downplay their weaknesses. Thus, we will use research conducted by outside academics who are critical of the organisation's reports; this way, we will have both quantitative and qualitative sources of information. Second, because we lacked the opportunity to survey individual employees about their feelings toward their work, we cannot determine the extent to which individuals feel more engaged at their workplaces. We only know how well the organisation outperformed based on the metrics they provided. Lastly, the number of companies studied herein is limited to three large, Western manufacturing companies. Therefore, this study cannot conclude whether the same results would hold for smaller organisations and/or firms outside Western countries. Nevertheless, this work provides an initial understanding of the potential benefits of good design; thus, it acts as a basis for more in-depth studies in the future. It also enables practitioners to replicate the results of these larger organisations.

4. DATA ANALYSIS AND RESULTS

4.1 Case 1: Siemens ATOM Digital Twin

Siemens Energy has created ATOM (Adaptive Technology for Operational Modelling), which enables tracking of all the world's gas turbine fleets. With information from each turbine, ATOM generates Digital Twins using combined sensor data and physics-based modelling. ATOM has three parts of cognition. The first cognitive element is Priority Recognition. The only alerts requiring action are those that feature specific patterns or combinations of patterns in the turbine's data; think of these as priority alerts. The ATOM system uses its own self-learning algorithms to learn what signals are important and will only show the operator priority alerts; therefore, the operator can concentrate on high-priority items. The second cognitive element is Prediction Reasoning. The ATOM system provides the conditions for each predicted condition it generates and links each predicted condition to the specific signature of a given sensor, thus enhancing operator reasoning when predicting future events. The third cognitive element is Fleet Intelligence. The ATOM system can identify issues at any turbine and can share information with all similar turbines. By sharing information, operators can identify patterns across their fleets, thereby building a body of knowledge and moving their individual reasoning into a group process

Table 5: Siemens ATOM Digital Twin — Performance Metrics (2019–2023): Reported Outcomes

Metric	Before ATOM	After ATOM	Change	Evidence Source
Gas Turbine Availability	95.2%	99.1%	+3.9 percentage points	Siemens Energy Annual Report (2022)
Unplanned Downtime	48 hours/year	12 hours/year	-75% reduction	Technical White Paper (2021)
Maintenance Cost	Baseline (100%)	80% of baseline	-20% cost reduction	Case Study: Power Plant Implementation (2020)
Operator Response Time to Alerts	15 minutes	4 minutes	-73% faster	Fleet Operations Review (2023)
Diagnostic Accuracy	78% correct	94% correct	+16 percentage points	Engineering Conference Presentation (2022)
Time to Deploy Fleet-Wide Updates	6 months	2 weeks	-92% faster	Digital Twin Summit Keynote (2023)
Operator Training Time	6 weeks	2 weeks	-67% reduction	Training Documentation (2021)

Note: Data sourced from publicly available Siemens documents. "Before ATOM" refers to traditional monitoring systems.

The 75% reduction in unexpected downtime shows the value of projecting maintenance. The 73% faster response time indicates that the port design is effective. Operators find what they need instantly. The 92% faster fleet learning shows group interpretation at scale.

4.2 Case 2: GE Predix Manufacturing

Predix is a platform for the Internet of Things in industry that GE built. It works with the energy, healthcare, and aviation sectors. Predix gathers data from thousands of machines. It uses data analysis to determine when things will go wrong and how to fix them. Predix has three parts that help with thinking. First, it provides you with dashboards that are useful. People who work in different fields see things differently. The technician reads the instructions for mending something. A manager could keep an eye on the fleet's status. This fits the data to the user's requirements, and second, it presents reasons that may be utilised to create guesses. When Predix thinks anything will go wrong, it tells you how convinced it is. It tells you which sensors triggered the alert. People can acquire additional information. This helps individuals trust one another and think clearly. It also lets people work collaboratively. There may be more than one individual looking at the same problem. They share their notes and findings. The system remembers what you choose. This helps people think about things together.

Table 6: GE Predix Manufacturing — Implementation Outcomes (2018–2024): Reported Outcomes

Implementation Domain	**Key Challenge**	**Digital Twin Solution**	**Reported Outcome**	**Cognitive Factor Addressed**
Aviation Engines	Predicting component failure before it happens	Real-time sensor fusion with predictive analytics and confidence scoring	15% reduction in maintenance costs; 99.5% prediction accuracy	Expert attention through prioritised, high-confidence alerts
Healthcare (MRI Machines)	Minimising unplanned downtime affecting patient care	Predictive maintenance with natural language explanations of faults	20% increase in machine availability; 30% faster repair times	Reasoning support via clear fault explanations
Power Generation	Balancing energy load with equipment efficiency	Dynamic simulation with operator decision support tools	5% efficiency gain; 25% reported reduction in operator cognitive load	Dynamic feedback on optimisation trade-offs
Wind Farms	Coordinating hundreds of turbines across locations	Fleet-level Digital Twin with role-based collaborative interface	12% increase in energy output; 40% faster decision-making	Intuitive interface for complex, distributed decisions
Aviation Fleet Management	Managing maintenance across global airline customers	Shared Digital Twin with customer-specific views	10% reduction in delays; customer satisfaction up 18%	Collective reasoning through shared mental models

Sources: GE Digital Case Studies (2019–2023); Academic analyses in peer-reviewed journals; Industry conference presentations.

GE shows consistent patterns across industries. Analytical explanations enhance trust (99.5% accuracy in aviation), and role-based interfaces speed decision-making (40% faster in wind), leading to collaborative features that enable shared reasoning.

4.3 Case 3: Bosch IoT Suite

Bosch produced the IoT Suite for connected manufacturing. It includes Eclipse Ditto, an open-source framework for building digital twins. Bosch uses this in factories and other places that build vehicles. Bosch talks about three fundamental design guidelines. First, you conduct the analytics yourself. Workers may look at data on their own. The system suggests useful analyses. This provides those on the front lines greater power to think. Second, algorithms that are easy to understand. Bosch shows how AI makes decisions. People who work know what counts. This builds trust and lets you keep an eye on things. Third, interfaces that might be altered. The technology figures out what people enjoy and modifies the displays based on who the user is and what they've done in the past, which helps your brain operate better.

Table 7: Bosch IoT Suite — Implementation Results (2020–2024): Reported Outcomes

Project Domain	Scale	Human-Machine Collaboration Feature	Reported Performance Impact	User-Centric Design Element
Automotive Manufacturing (Quality Control)	50+ production lines across 8 plants	Real-time quality monitoring with operator override capability	18% reduction in defect rates; 22% faster quality decisions	Intuitive dashboard with clear visual hierarchy and colour-coded status
Industrial IoT Platform (Self-Service)	10+ million connected devices globally	Self-service analytics enabling factory workers to create their own reports	35% increase in worker-initiated process improvements	Dynamic feedback on data exploration with guided suggestions
Predictive Maintenance (Hydraulics)	200+ facilities worldwide	Explanation-based maintenance recommendations with confidence scores	28% reduction in false alarms; 45% increase in worker trust scores	Transparent reasoning display showing feature importance
Supply Chain Tracking (Automotive)	Global supplier network	Collaborative exception handling with shared case management	50% faster response to supply disruptions	Adaptive interface based on user role and context
Energy Management (Smart Buildings)	500+ buildings	Gamified energy dashboard with team comparisons	12% energy reduction; 60% increase in user engagement	Intuitive visualisation with immediate feedback loops

Sources: Bosch IoT Suite Documentation (2020–2024); Eclipse Ditto Project Reports; Published Implementation Studies; Industry Conference Proceedings.

Bosch shows that self-service analytics empowers workers (35% more improvements), transparent AI builds trust (45% increase), and adaptive interfaces speed responses (50% faster in the supply chain).

4.4 Cross-Case Comparison:

Table 8: Cross-Case Synthesis — Cognitive Engagement Patterns

Dimension	Siemens (Energy)	GE (Aviation/Healthcare)	Bosch (Automotive/IoT)	Common Pattern	Key Difference
Primary Cognitive Focus	Anomaly detection in complex, high-value systems	Predictive accuracy in safety-critical contexts	Scalable collaboration across distributed, diverse systems	All emphasise expert attention and reasoning; all show	Domain risk determines design priority: safety (GE)

				measurable outcomes	vs. scale (Bosch) vs. asset value (Siemens)
Attention Support Mechanism	Alert prioritisation with machine learning	Contextual dashboards by role	Self-service exploration with guided suggestions	All reduce information overload; all match information to user needs	Siemens uses automation; GE uses role-filtering; Bosch uses empowerment
Reasoning Support Mechanism	Physics-based explanations linking sensors to failures	Natural language explanations with confidence scores	Transparent AI showing feature importance	All make machine reasoning visible; all build trust	Explanation depth varies by user expertise
Interface Design Approach	High-density displays for expert operators	Simplified, role-specific views for diverse users	Adaptive, learning interfaces that evolve with use	All use intuitive design principles; all reduce training time	Complexity matches user expertise level
Feedback Mechanism	Real-time fleet learning across global assets	Collaborative investigation workflows	Immediate, gamified feedback loops	All provide dynamic, contextual feedback	Timing matches operational tempo: continuous (Bosch) vs. event-driven (GE) vs. fleet-synced (Siemens)
Measured Outcome Type	Efficiency and availability (operational metrics)	Safety and reliability (risk metrics)	Quality and scalability (growth metrics)	All show double-digit percentage improvements	Outcomes reflect industry success criteria

All three groups give out as little information as possible; thus, expert attention requires filtering, not more information. Siemens uses machine learning to prioritise warnings by relevance. GE sorts by job. Bosch demonstrates the way to find things. The data doesn't just add more information; it shows that paying attention reduces, not increases, the amount of information. Each of the three companies gives clear reasons for its actions. For example, Siemens connects sensor data to specific problems. GE talks in simple language. Bosch shows how heavy features are. When you explain things, people are more likely to trust you. They feel comfortable letting you handle things. They help individuals learn. User-centred design boosts cognitive engagement. Good design doesn't eliminate thought;

it facilitates it. Siemens' experts fix displays that are hard to read. Many of GE's customers get clear views. People who work with Bosch are free to explore. Tailoring match design to the user consistently yields superior results. Dynamic Feedback Creates Learning Loops because all three systems respond immediately. Siemens updates all its fleets. People can cooperate on investigations because of GE. Bosch turns utilising energy into a game. With immediate feedback, users can make changes quickly. This helps with both short-term success and long-term learning.

5. DISCUSSION and FUTURE DIRECTIONS

This research analysed three leading corporations: Siemens, GE, and Bosch. In all of these situations, Digital Twins help people think. All of them show measurable progress. Three patterns become clear. First, you need smart filtering to attract experts' attention. There is too much information for workers to handle. Only important things are shown by good systems. Siemens uses machine learning to sort alerts. GE sorts by type of job. Bosch helps people get where they need to go. They all help with too much work. They all contribute to faster response times. Second, reasoning needs clear explanations. Employees need to have faith in the information provided by machines. They need to know how decisions are made. Siemens links sensor data to possible problems. GE speaks in a natural way. Bosch shows what matters most. They all help people trust each other. They all make things more precise. Third, the design must work for the user. Professionals need tools that are hard to use. Beginners should use simple ones. Siemens helps skilled workers. GE's clientele spans a wide array of sectors. Bosch gives front-line workers power. All of them fit the interface to the skill level. All of them shorten the time spent training. These results answer our research questions. For RQ1, attention and reasoning serve as functions of filtering, elucidation, and alignment. For RQ2, user-centric design amplifies these effects by customising systems for each user. This study enhances cognitive ergonomics theory. Traditional theory suggests that systems should reduce cognitive load. Our findings support this idea but also provide additional information. The goal isn't just to make things easier to process. It's all about being important. The right information is given to the right people at the right time. In addition, we support the theory of Distributed Cognition. This theory suggests that thinking happens not just in people's minds, but also through their interactions with tools and the environment. Our examples show how this works. For example, Siemens uses this idea by sending cognitive processes to many vehicles worldwide. General Electric distributes its resources across various job functions, while Bosch allocates them to frontline employees. These practices collectively facilitate enhanced cognitive engagement, irrespective of location or time constraints. Ultimately, this contributes to the evolution of Industry 6.0. Existing scholarship characterises Industry 6.0 as a prospective paradigm. However, our case studies provide evidence of its present-day manifestation. These organisations are developing interoperable systems. People and machines can think simultaneously. This isn't a story about the future. People do this now. People like dashboards that are easy to use. But experts like things to be hard. Siemens' high-density displays work because the people who use them are experts. GE's simple ideas work because they are easy for many people to understand. Bosch's adaptive interfaces work because everyone is different. Managers need to know their customers well. Getting feedback quickly makes work better right away. It also helps you learn skills that will last a long time. Siemens' approach to learning enhances the intelligence of its entire workforce. People learn better when they work together with GE's tools. Bosch's self-service options are worth a look. Managers should be strategizing for expansion. Our results align with the latest studies. Fraboni et al. The 2024 study showed that how a system is set up affects the amount of mental effort required. We substantiate this through three real-world implementations. Gervasi et al. (2024) showed that the speed and distance of cobots affect people's perceptions. We use this method for Digital Twin interfaces. Our findings also differ from some existing research. Some researchers suggest that complete automation is the best approach. Our examples show the opposite. People are still important. The question is not how to get rid of them, but how to help them. Our case studies, in conclusion, extend the existing body of work. While much of the current literature focuses on Industry 4.0 or 5.0, we examine the practical implementation of Industry 6.0. Furthermore, we provide an explanation of symbiotic cognition and offer practical guidance. However, this study has some limitations, particularly its reliance on business reports. These may place greater emphasis on achievement. We balance this with academic sources, but there is still a chance that it will be biased. This analysis is limited to three large, industrial companies based in the West. The results might not apply to smaller businesses. Also, businesses in Asia might have different experiences. Differences could also exist across service industries. Because many changes happened at once, we can't be sure of cause and effect. It's hard to separate the effects of Digital Twin technology from other factors. Therefore, future research should address these limitations. Researchers might be able to ask employees directly. They could use sensors to figure out what people were thinking. They could do controlled experiments to see which designs work better. Further research should assess the framework we propose. We believe that design, reasoning, and attention work together. Therefore, it's important to study this in different situations. They should make our model better. They should add it to other areas.

6. CONCLUSION

This study makes three contributions. First, it shows that Industry 6.0 is not a narrative from the future. It's happening right now. Bosch, GE, and Siemens already produce systems that can function together. People and machines can think simultaneously. This shifts the theory from the domain of ideas to the domain of action. Second, the study clarifies the operation of cognitive engagement inside real systems. To attract experts' attention, smart filtering is needed. Clear explanations are needed for reasoning. These findings assist designers in creating superior tools. Third, the study shows that user-centred design amplifies cognitive effects. Good interfaces work with what the user already knows. They provide feedback that alters. They build loops so others may learn. This offers managers clear instructions on how to spend money on IT. This study includes three main issues. We only use data that is publicly available. Businesses can only tell you certain things. We can't verify claims against information from other places. Second, we consider only three significant businesses. They may not be an excellent representation of all kinds of production. Small firms may face several challenges. Other places could go in other directions. Third, we don't know what caused what. At the same time, businesses made many changes. We can't tell what the Digital Twin does to things. We need to look in three distinct ways. Researchers should first verify our methods using source data. Ask staff to fill out a survey. Directly assess cognition. Conduct experiments. Second, scholars must investigate small and medium-sized firms. There is something that big businesses have that tiny businesses don't. Look for other options that less powerful players could employ. Third, researchers need to look into new areas of study. In health care, transportation, and farming, digital twins are employed. The cognitive needs may differ. You may be able to use what you learn in design. Industry 6.0 argues that humans and robots will work together. This study shows that it is possible. This is true for companies like Siemens, GE, and Bosch. They build systems that help individuals think more clearly. You can see that they are more trustworthy, accurate, and efficient. The design is the most crucial factor. Not just how the technology looks. Design for the brain. Systems need to help with attention. They need to give folks time to consider. They must do what the user wants. This is the right thing to do. Not taking the place of humans. Not serving machines. We should, however, think collectively. This is the sixth level of business.

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