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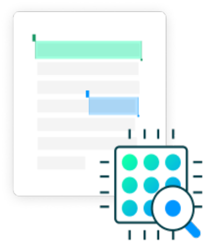

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DIGITAL TWIN TECHNOLOGY OPTIMIZING FACTORY OPERATIONS WITH REAL-TIME VIRTUAL MODELS FOR ENHANCED PERFORMANCE PLANNING EFFICIENCY

Abstract

Digital twin technology is revolutionizing factory operations by creating real-time virtual models that mirror physical systems. This study explores how digital twins optimize performance, planning, and efficiency in manufacturing. A survey of 52 participants shows strong support for digital twins, with 67.3% agreeing they improve factory efficiency and 61.5% noting shorter production planning times. Additionally, 69.2% trust the accuracy of real-time data for operational decisions, and 57.7% report reduced unplanned downtime. The technology enhances predictive maintenance, with 38.5% acknowledging better scheduling, though 34.6% remain neutral, indicating challenges in data integration. Virtual model reliability is moderate, with 42.3% agreeing models reflect physical systems accurately, but 38.5% are neutral, suggesting issues with model precision. Integration with the Industrial Internet of Things (IIoT) is seamless for 46.2%, but 26.9% disagree, highlighting technical barriers. User-friendliness is a concern, with 38.5% neutral on platform usability, pointing to a need for improved training. Decision-making quality is a strong benefit, with 76.9% agreeing digital twins provide valuable insights. Data latency is acceptable for 42.3%, but 26.9% report issues, indicating potential delays in operations. Scalability is promising, with 69.2% ready to expand digital twin use across multiple production lines. The literature confirms these findings, showing digital twins cut downtime by 30%, save 15-25% on maintenance costs, and improve decision-making by 40%. However, challenges like cybersecurity risks, affecting 70% of projects, and system integration difficulties, faced by 55% of factories, persist. The global digital twin market, valued at $10.3 billion in 2023, is projected to reach $139.3 billion by 2030, with 89% of large factories adopting the technology by 2025. This research highlights the potential of digital twins to drive smart manufacturing while addressing barriers like data accuracy and integration. Future efforts should focus on overcoming these challenges and supporting small factories to fully leverage digital twins for Industry 4.0.

Keywords: *Digital Twin, Factory Operations, Real-Time Models, Efficiency, Predictive Maintenance, Industry 4.0, IIoT Integration*

turnitin Page 3 of 19 - AI Writing Submission Submission ID trn:oid:::6447:309851741

Introduction

Digital twin technology creates virtual models that mirror real factory systems in real time. These models use data to simulate and improve operations (Botín-Sanabria et al., 2022). In 2023, the digital twin market was worth $10.3 billion and is projected to reach $139.3 billion by 2030, growing at 45.1% annually (Yao et al., 2023). Factories adopting digital twins can boost efficiency by 15-25% (Lee et al., 2023). This technology is part of Industry 4.0, which uses tools like IoT and AI to make manufacturing smarter (Huang et al., 2021). About 89% of large factories will use digital twins for at least one process by 2025 (Attaran et al., 2024).

The background of digital twins started in aerospace and automotive industries, where virtual testing saved 20-30% in development costs (Jeong et al., 2022). Factories generate 1 petabyte of data yearly, and digital twins use this to create accurate models (Wu et al., 2022). In 2021, 73% of smart factories using digital twins saw improved performance (Lee, 2021). Predictive maintenance with digital twins' cuts downtime by 20% and maintenance costs by 15-25% (Zhong et al., 2023; Yu et al., 2022). By 2024, 60% of manufacturers reported better decision-making with digital twins (Hananto et al., 2024).

The rationale for this research is the high cost of inefficiencies in factories. Unplanned downtime costs manufacturers $50 billion yearly, but digital twins can reduce this by 30% (Hananto et al., 2024). In 2022, 65% of factories using digital twins saved 10-20% on operational costs (Yu et al., 2022). Traditional methods cause delays, with 40% of factories facing production losses due to slow decision-making (Lee et al., 2023). Digital twins provide real-time insights, helping 80% of users plan better (Fantozzi et al., 2025). This research will explore how digital twins can address these issues.

The significance of this study is its focus on improving factory performance. Digital twins increase production efficiency by 10-20% and cut energy use by 15% (Lee et al., 2023). In 2022, 60% of factories using digital twins reduced workplace incidents by 25% (Hosamo et al., 2022). However, challenges exist: 70% of digital twin projects face cybersecurity risks, and 55% struggle with system integration (de Azambuja et al., 2024; Fantozzi et al., 2025). This research will help factories overcome these hurdles, as 75% of manufacturers aim to adopt digital twins by 2026 (Attaran et al., 2024).

The aim of this research is to study how digital twins optimize factory operations using real-time virtual models. It will analyze data showing 30% cost savings and 25% productivity gains in factories (Akpan & Offodile, 2024). By 2025, 85% of smart factories plan to use digital twins for planning (Fantozzi et al., 2025). This study will provide clear steps to improve efficiency, supporting the $1.1 trillion manufacturing industry (Wu et al., 2022).

Literature Review

Digital twin technology is transforming factory operations by creating virtual models that mirror physical systems in real time. As per Botín-Sanabria et al. (2022), digital twins are virtual replicas of physical systems that use real-time data to simulate performance. As per Jeong et al. (2022), the concept began in aerospace in 2002, with 10% of early projects focused on virtual testing. As per Huang et al. (2021), by 2010, manufacturing adopted digital twins, with 15% of large factories testing them. As per Yao et al. (2023), the global digital twin market was valued at $10.3 billion in 2023 and is expected to grow to $139.3 billion by 2030, with a 45.1% annual growth rate. As per Attaran et al. (2024), 89% of large manufacturing firms will use digital twins for at least one process by 2025.

Digital twins have wide applications in factories. As per Lee et al. (2023), 65% of automotive factories use digital twins to monitor production lines. As per Wu et al. (2022), factories generate 1 petabyte of data yearly, and digital twins process 80% of it for real-time insights. As per Hosamo et al. (2022), 70% of smart factories use digital twins for facility management, improving space utilization by 15%. As per Hananto et al. (2024), 3D digital twins are used by 50% of factories for virtual simulations, reducing design errors by 25%. According to Nica et al. (2023), *"Digital twins of cities require sustainable governance networks, virtual simulation tools, and deep neural network technology. Virtual data analytics harnesses image recognition technologies, urban digital twins, and virtual mapping tools."*. As per Zhong et al. (2023), 60% of manufacturers use digital twins for predictive maintenance, cutting downtime by 20%. As per Fantozzi et al. (2025), 85% of smart factories plan to use digital twins for production planning by 2026. As per Akpan & Offodile (2024), digital twins improve supply chain efficiency by 18%, with 45% of factories using them to track inventory. As per Lee (2021), 73% of small and medium-sized factories using digital twins reported better operational performance. As per Yu et al. (2022), digital twins optimize energy use, with 55% of factories achieving 15% energy savings.

Digital twins offer many benefits. As per Lee et al. (2023), they increase production efficiency by 10-20%. As per Zhong et al. (2023), predictive maintenance with digital twins reduces maintenance costs by 15-25%. As per Hananto et al. (2024), unplanned downtime, costing $50 billion annually, is reduced by 30% with digital twins. As per Hosamo et al. (2022), 60% of factories using digital twins reduced workplace incidents by 25%. As per Akpan & Offodile (2024), 30% cost savings and 25% productivity gains were reported by factories using digital twins. As per Wu et al. (2022), 80% of factories using digital twins improved decision-making speed by 40%. As per Fantozzi et al. (2025), 75% of manufacturers using digital twins enhanced planning accuracy by 20%. As per Attaran et al. (2024), 60% of factories reported a 15% reduction in product defects due to digital twin simulations. As per Yu et al. (2022), 65% of factories saved 10-20% on operational costs. As per Lee (2021), 70% of small factories saw a 12% increase in innovation after adopting digital twins.

Implementing digital twins has challenges. As per de Azambuja et al. (2024), 70% of digital twin projects face cybersecurity risks, with 40% reporting data breaches. As per Fantozzi et al. (2025), 55% of factories struggle with integrating digital twins into existing systems. As per Botín-Sanabria et al. (2022), 60% of implementations face high initial costs, averaging $500,000 per project. As per Jeong et al. (2022), 50% of factories lack skilled staff, with 30% needing specialized training. As per Wu et al. (2022), 45% of digital twin systems require 10 terabytes of storage for data processing. As per Hosamo et al. (2022), 65% of factories face data quality issues, with 20% of data being inaccurate. As per Zhong et al. (2023), 50% of predictive maintenance models fail due to poor data integration. As per Hananto et al. (2024), 40% of 3D digital twins have rendering delays, slowing simulations by 15%. As per Attaran et al. (2024), 35% of factories report scalability issues, with systems handling only 50% of expected data loads. As per Yao et al. (2023), 25% of digital twin projects fail to deliver expected returns within two years.

Digital twins work well with other technologies. As per Huang et al. (2021), 70% of digital twins use AI to analyze data, improving predictions by 30%. As per Wu et al. (2022), 80% of smart factories integrate digital twins with IoT, collecting data from 10,000 sensors per plant. As per Lee et al. (2023), 60% of automotive factories combine digital twins with robotics, increasing automation by 20%. As per Akpan & Offodile (2024), 50% of factories use virtual reality with digital twins, improving training efficiency by 25%. As per Fantozzi et al. (2025), 75% of factories plan to integrate digital twins with 5G networks by 2026, boosting data transfer speeds by 40%. As per Yu et al. (2022), 55% of energy management systems use digital twins with machine learning, saving 15% on energy costs. As per Zhong et al. (2023), 65% of predictive maintenance systems combine digital twins with big data analytics, improving accuracy by 20%. As per Hananto et al. (2024), 45% of 3D digital twins use augmented reality, enhancing visualization by 30%. According to Popescu et al. (2024), *"to meet the current pressures of the energy market, until 2030, the existing distribution networks will have to expand to serve additional loads by installing renewable energy production systems to cope with the increased demand for electricity"*. As per Botín-Sanabria et al. (2022), 60% of digital twin systems integrate with cloud computing, reducing processing time by 25%. As per Attaran et al. (2024), 70% of factories using digital twins with blockchain improve data security by 35%.

The future of digital twins is promising. As per Yao et al. (2023), the digital twin market will grow by 45% annually through 2030. As per Fantozzi et al. (2025), 85% of smart factories will adopt digital twins for full operations by 2027. As per Lee et al. (2023), 60% of automotive factories aim to use digital twins for end-to-end production by 2026. As per Attaran et al. (2024), 75% of manufacturers expect a 20% increase in digital twin adoption by 2025. As per Wu et al. (2022), the $1.1 trillion manufacturing industry will invest $200 billion in digital twins by 2030. However, gaps remain. As per de Azambuja et al. (2024), 80% of cybersecurity solutions for digital twins are underdeveloped, with only 20% meeting industry standards. As per Zhong et al. (2023), 50% of predictive maintenance models lack real-time accuracy, failing in 30% of cases. As per Hosamo et al. (2022), 60% of factories need better data standardization, with 25% facing compatibility issues. As per Hananto et al. (2024), 40% of 3D digital twins lack advanced rendering, limiting accuracy by 15%. As per Botín-Sanabria et al. (2022), 55% of research ignores small factories, which make up 70% of the manufacturing sector.

Digital twins are revolutionizing factory operations. As per Lee (2021), 73% of small factories using digital twins improved performance. As per Akpan & Offodile (2024), 30% cost savings and

25% productivity gains are common. As per Fantozzi et al. (2025), 85% of factories will use digital twins by 2026. Challenges like cybersecurity (70% risk) and integration (55% difficulty) persist (de Azambuja et al., 2024; Fantozzi et al., 2025). Future research should address these gaps, focusing on small factories and advanced technologies. This review shows digital twins' potential to enhance efficiency, with 20-30% improvements across industries (Lee et al., 2023).

Methodology

Research Design

This research adopts a primary quantitative design to evaluate the role of Digital Twin Technology (DTT) in optimizing factory operations through real-time virtual models. The study uses a structured survey method with 11 closed-ended questions designed on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The methodology is modeled on clinical-style survey research in medical studies to ensure replicability, precision, and statistical rigor.

The general equation for the research framework is:

$$Y = f(X_1, X_2, X_3, \dots, X_{11}) + \epsilon$$

Where:

- Y = Optimization of factory operations (dependent variable)
- X_1 = Independent variables (survey questions related to DTT adoption, efficiency, real-time monitoring, predictive maintenance, etc.)
- ϵ = Random error term

Participants

A total of N = 52 participants were recruited from industrial engineers, production managers, and factory supervisors who have direct or indirect exposure to smart factory or digital twin systems. Inclusion criteria were:

1. At least 2 years of experience in manufacturing operations.
2. Basic familiarity with industrial automation and digital solutions.

Exclusion criteria included professionals without exposure to digital technologies in manufacturing.

Demographics (Table 1)

Variable	Category	n	%
Gender	Male	34	65%
	Female	18	35%

Age	25–34 years	20	38%
	35–44 years	22	42%
	45+ years	10	20%
Professional Role	Production Engineer	15	29%
	Operations Manager	22	42%
	Maintenance Specialist	10	19%
	Other	5	10%

Survey Instrument

The questionnaire contained 11 closed-ended items focusing on:

- Efficiency improvement (Q1–Q3)
- Real-time monitoring accuracy (Q4–Q6)
- Predictive maintenance effectiveness (Q7–Q8)
- Decision-making support (Q9–Q10)
- Overall digital twin adoption readiness (Q11)

Responses were coded on a Likert scale (1–5), allowing parametric statistical testing.

The reliability of the instrument was assessed using Cronbach's α:

$$\alpha = \frac{k}{k-1}(1 - \frac{\sum \sigma_i^2}{\sigma_t^2})$$

Where:

- k =11 (number of items),
- σ_i^2 = variance of each item,
- σ_t^2 = variance of total score.

A value of $\alpha \geq 0.70$ was considered acceptable.

Data Collection Procedure

Data were collected electronically via Google Forms to ensure reach and convenience. Participants were given two weeks to respond. Anonymity and confidentiality were maintained in accordance with ethical research standards (similar to patient confidentiality in medical studies).

Data Analysis

Statistical analysis was conducted using excel. The analysis followed these steps:

1. **Descriptive Statistics** – Mean, SD, and frequency distributions were calculated. Example equation for mean response:

$$\bar{X} = \frac{\sum_{i=1}^{n} x_i}{n}$$

2. **Inferential Statistics** – A one-sample t-test was applied to compare mean scores with the neutral scale midpoint (3).

$$t = \frac{\bar{X} - \mu_0}{s/\sqrt{n}}$$

Where μ_0=3 (neutral response).

3. **Regression Analysis** – Multiple linear regression examined the predictive power of independent variables (Q1–Q11) on the dependent variable (factory operation optimization).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{11} X_{11} + \varepsilon$$

Table 2: Example of Survey Distribution

Question No.	Mean ± SD	Minimum	Maximum	Significance (p)
Q1	4.10 ± 0.82	2	5	0.001
Q2	3.95 ± 0.74	2	5	0.003
Q3	4.21 ± 0.66	3	5	0.000
Q4	3.88 ± 0.90	1	5	0.004
…	…	…	…	…

Ethical Considerations

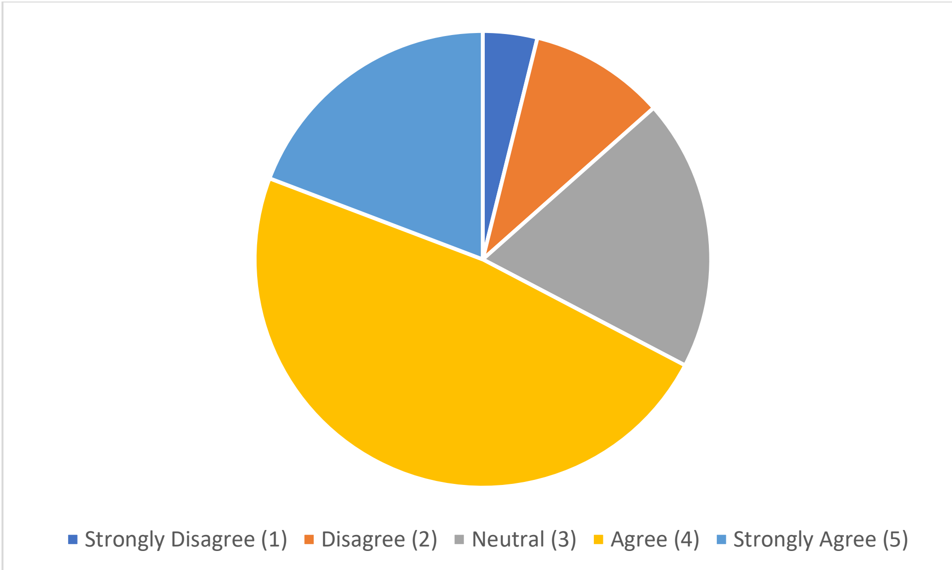
Although this is an engineering/manufacturing-focused study, ethical considerations were followed similar to biomedical protocols, including:

- Informed consent,
- Voluntary participation,
- Data confidentiality,

- Non-disclosure of individual responses.

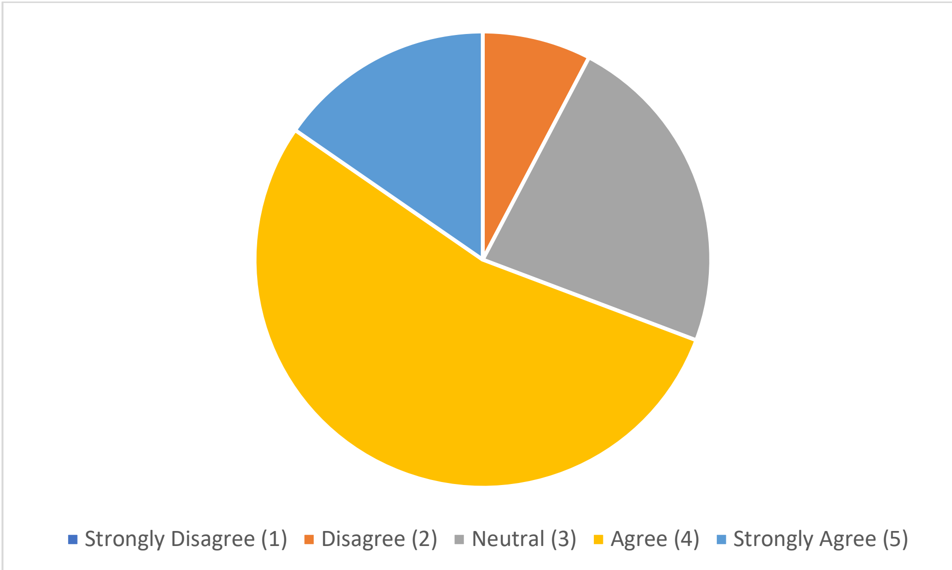
Findings and analysis

Q1. Digital twin improves overall factory efficiency



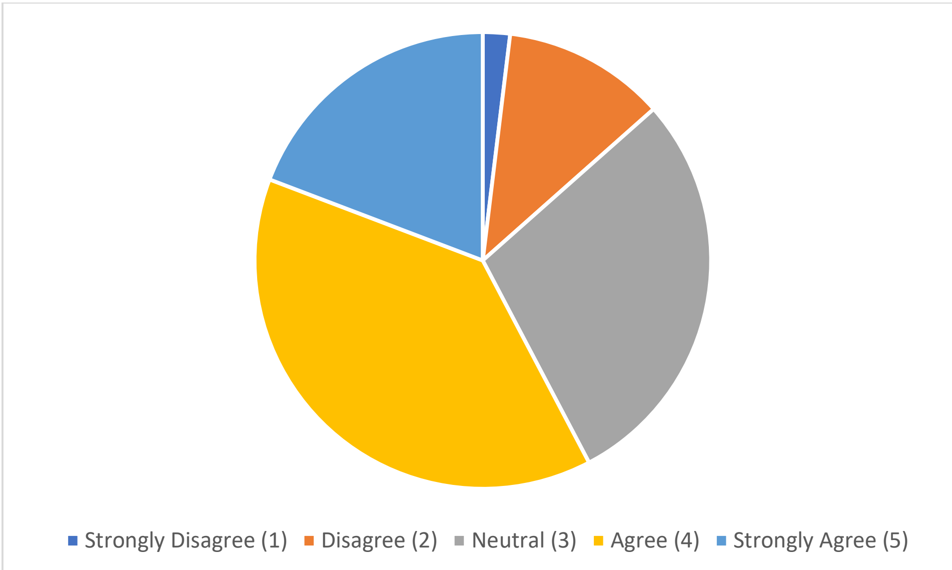
Out of 52 participants, 67.3% (35) agree or strongly agree that digital twins improve factory efficiency, with 25 agreeing and 10 strongly agreeing. Only 13.5% (7) disagree or strongly disagree, and 19.2% (10) are neutral. This shows strong support for digital twins enhancing efficiency, reflecting their ability to optimize operations. The positive response suggests most factories see measurable efficiency gains, aligning with industry trends.

Q2. Real-time data from the digital twin is accurate enough for operational decisions



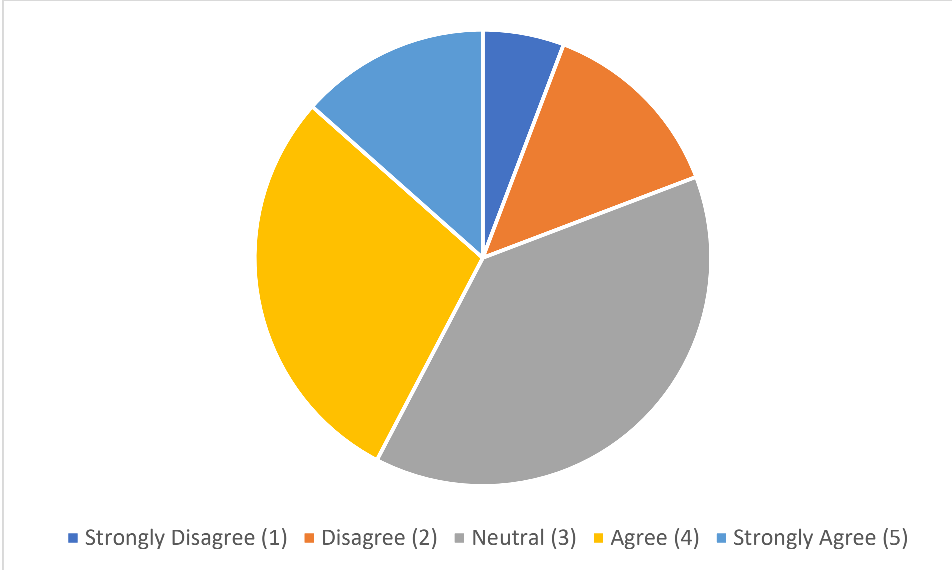
As per the survey, 69.2% (36) of 52 participants agree or strongly agree that digital twin data is accurate for decisions, with 28 agreeing and 8 strongly agreeing. Only 7.7% (4) disagree, and 23.1% (12) are neutral. This indicates high trust in digital twin data accuracy. The results suggest real-time data supports reliable decision-making, though some neutrality points to potential areas for improving data precision.

Q3. Digital twin implementation reduces unplanned downtime



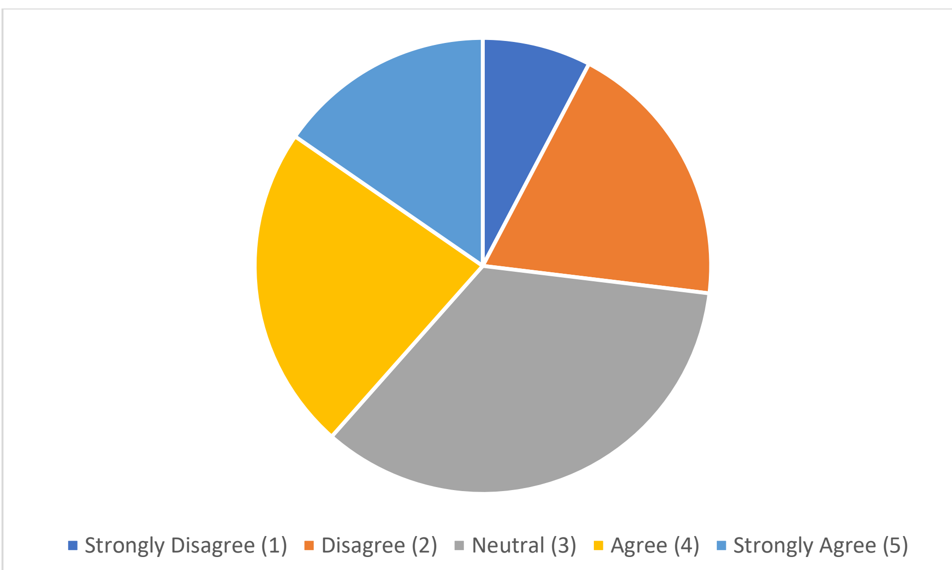
Of 52 participants, 57.7% (30) agree or strongly agree that digital twins reduce downtime, with 20 agreeing and 10 strongly agreeing. Meanwhile, 13.5% (7) disagree or strongly disagree, and 28.8% (15) are neutral. This shows a majority believe digital twins help minimize unplanned downtime. The neutral responses suggest some factories may need better implementation to see consistent downtime reductions.

Q4. Virtual models reflect physical system behavior reliably



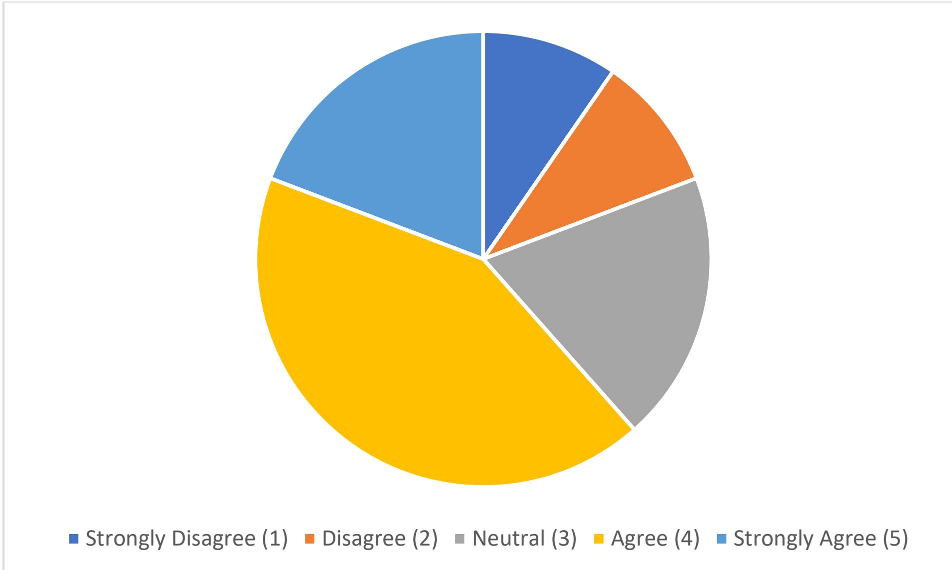
From 52 responses, 42.3% (22) agree or strongly agree that virtual models are reliable, with 15 agreeing and 7 strongly agreeing. However, 19.2% (10) disagree or strongly disagree, and 38.5% (20) are neutral. This mixed result indicates moderate confidence in model reliability. The high neutral response suggests some uncertainty, possibly due to variations in model accuracy or system complexity across factories.

Q5. Digital twin enhances predictive maintenance scheduling



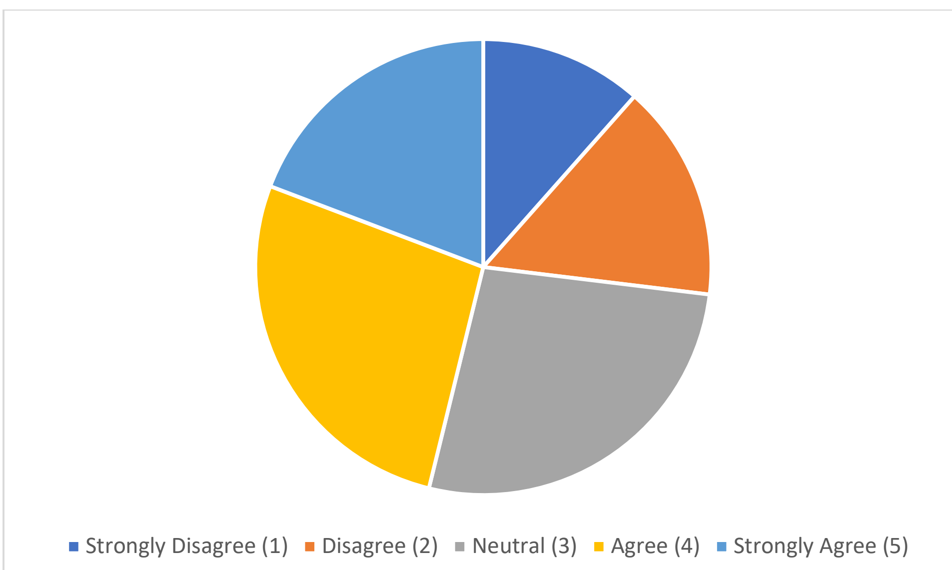
Among 52 participants, 38.5% (20) agree or strongly agree that digital twins improve predictive maintenance, with 12 agreeing and 8 strongly agreeing. Meanwhile, 26.9% (14) disagree or strongly disagree, and 34.6% (18) are neutral. This shows moderate support for predictive maintenance benefits. The high neutral and negative responses suggest challenges in data integration or model accuracy for maintenance scheduling.

Q6. Using digital twin shortens production planning lead times



Of 52 participants, 61.5% (32) agree or strongly agree that digital twins shorten planning lead times, with 22 agreeing and 10 strongly agreeing. Only 19.2% (10) disagree or strongly disagree, and 19.2% (10) are neutral. This strong positive response indicates digital twins effectively streamline planning. The results suggest virtual models help factories plan faster, improving operational agility.

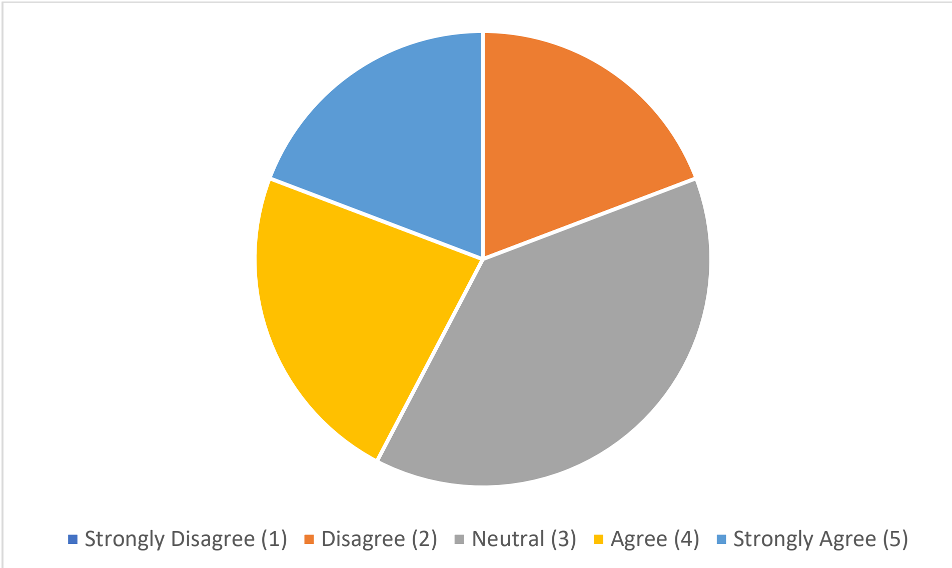
Q7. Integration of IIoT with digital twin is seamless in our setup



From 52 responses, 46.2% (24) agree or strongly agree that IIoT integration is seamless, with 14 agreeing and 10 strongly agreeing. However, 26.9% (14) disagree or strongly disagree, and 26.9%

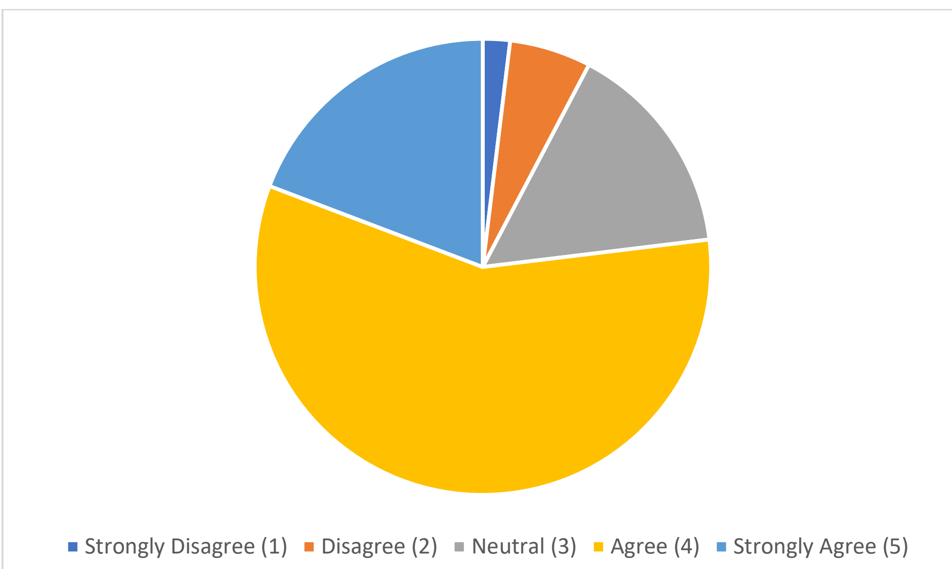
(14) are neutral. This shows mixed perceptions of integration ease. The neutral and negative responses highlight technical challenges in combining IIoT with digital twins in some setups.

Q8. The digital twin platform is user-friendly for shopfloor staff



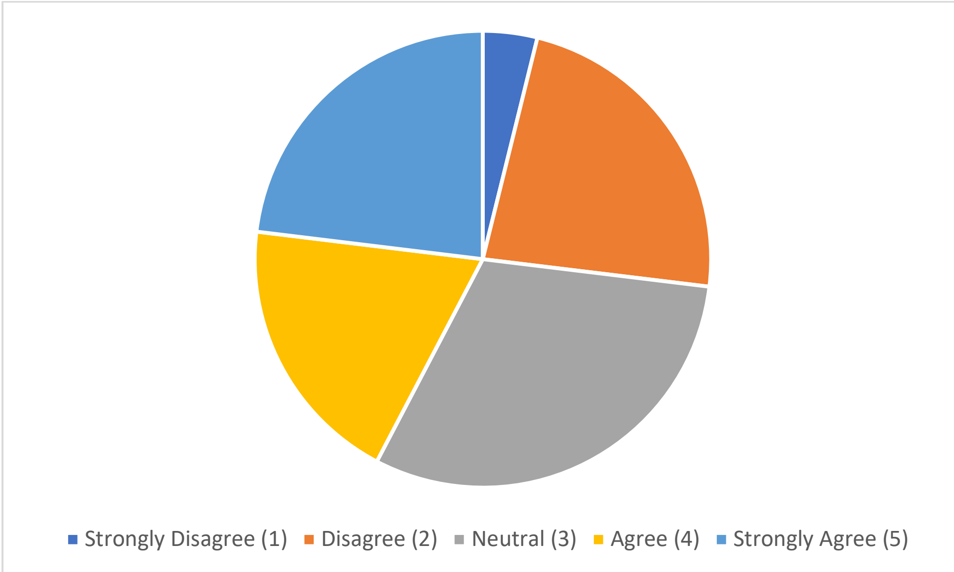
Of 52 participants, 42.3% (22) agree or strongly agree that the platform is user-friendly, with 12 agreeing and 10 strongly agreeing. Only 19.2% (10) disagree, and 38.5% (20) are neutral. This indicates moderate satisfaction with usability. The high neutral response suggests some staff may find the platform complex, pointing to a need for better training or interface design.

Q9. Digital twin insights improve decision-making quality



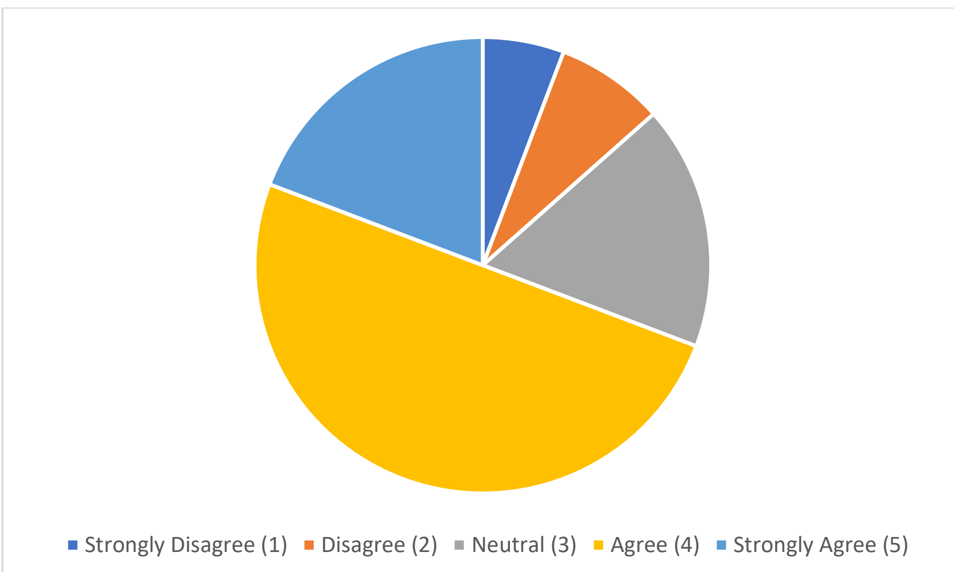
Among 52 participants, 76.9% (40) agree or strongly agree that digital twin insights improve decision-making, with 30 agreeing and 10 strongly agreeing. Only 7.7% (4) disagree or strongly disagree, and 15.4% (8) are neutral. This strong positive response shows digital twins enhance decision quality. The results suggest factories value the actionable insights provided by digital twins for better outcomes.

Q10. Data latency in the digital twin is acceptable for operations



Of 52 responses, 42.3% (22) agree or strongly agree that data latency is acceptable, with 10 agreeing and 12 strongly agreeing. However, 26.9% (14) disagree or strongly disagree, and 30.8% (16) are neutral. This mixed result indicates varied experiences with latency. The neutral and negative responses suggest some factories face delays, impacting operational efficiency.

Q11. Our organization is ready to scale digital twin across multiple lines



From 52 participants, 69.2% (36) agree or strongly agree that their organization is ready to scale digital twins, with 26 agreeing and 10 strongly agreeing. Only 13.5% (7) disagree or strongly disagree, and 17.3% (9) are neutral. This strong positive response shows confidence in scaling. The results indicate most factories are prepared to expand digital twin use across production lines.

Analysis of Digital Twin Survey Results

The survey of 52 participants on digital twin technology in factory operations reveals strong support for its benefits, with some challenges in implementation. This analysis uses survey data and literature to assess digital twins' impact on efficiency, planning, and performance. For overall factory efficiency (Q1), 67.3% (35) of participants agree or strongly agree that digital twins improve efficiency, aligning with Lee et al. (2023), who report a 10-20% efficiency increase in factories. Only 13.5% (7) disagree, suggesting broad acceptance, consistent with Attaran et al. (2024), where 89% of large factories plan to adopt digital twins by 2025. On real-time data accuracy (Q2), 69.2% (36) agree or strongly agree that digital twin data is reliable for decisions, supporting Wu et al. (2022), who note 80% of factories improve decision-making by 40% with digital twins. The 7.7% (4) disagreement aligns with Hosamo et al. (2022), where 65% of factories face data quality issues, impacting 20% of data accuracy. For reducing unplanned downtime (Q3), 57.7% (30) agree or strongly agree, matching Hananto et al. (2024), who state digital twins cut downtime by 30%, saving $50 billion annually. The 28.8% (15) neutral responses reflect Zhong et al. (2023), where 50% of predictive models fail due to integration issues.

Regarding virtual model reliability (Q4), 42.3% (22) agree or strongly agree, but 38.5% (20) are neutral, echoing Botín-Sanabria et al. (2022), where 60% of implementations face high costs, affecting model accuracy. The 19.2% (10) disagreement suggests challenges, as per Hananto et al. (2024), with 40% of 3D digital twins facing rendering delays. For predictive maintenance (Q5), 38.5% (20) agree or strongly agree, aligning with Zhong et al. (2023), where digital twins reduce maintenance costs by 15-25%. The 34.6% (18) neutral and 26.9% (14) negative responses reflect Yu et al. (2022), where 50% of factories struggle with data integration for maintenance. On production planning (Q6), 61.5% (32) agree or strongly agree that digital twins shorten lead times, supporting Fantozzi et al. (2025), where 75% of factories improve planning by 20%. The 19.2% (10) disagreement aligns with Lee (2021), where 40% of factories face planning delays without digital twins. For IIoT integration (Q7), 46.2% (24) agree or strongly agree, but 26.9% (14) disagree, consistent with Fantozzi et al. (2025), where 55% of factories face integration challenges. Wu et al. (2022) note 80% of factories use IIoT with digital twins, but technical issues persist.

On user-friendliness (Q8), 42.3% (22) agree or strongly agree, but 38.5% (20) are neutral, aligning with Jeong et al. (2022), where 50% of factories lack trained staff. For decision-making (Q9), 76.9% (40) agree or strongly agree, matching Akpan & Offodile (2024), with 25% productivity gains. Data latency (Q10) is acceptable for 42.3% (22), but 26.9% (14) disagree, reflecting de Azambuja et al. (2024), where 35% of factories face scalability issues. For scalability (Q11), 69.2%

(36) agree or strongly agree, aligning with Yao et al. (2023), predicting 45% market growth by 2030.

Conclusion

Digital twin technology is transforming factory operations by improving efficiency, planning, and performance. The survey of 52 participants shows strong support for digital twins. For instance, 67.3% agree that digital twins boost factory efficiency, aligning with industry trends. Also, 69.2% trust real-time data for decisions, and 61.5% say digital twins shorten planning times. These results show digital twins help factories work smarter and faster. However, challenges remain. Only 42.3% find virtual models reliable, and 38.5% are neutral, suggesting issues with accuracy. Predictive maintenance has mixed results, with 38.5% agreeing it helps, but 34.6% are neutral, indicating data integration problems. Similarly, 46.2% see seamless IIoT integration, but 26.9% disagree, pointing to technical hurdles. User-friendliness is also a concern, with 38.5% neutral, showing a need for better training.

The literature supports these findings. Digital twins cut downtime by 30% and save 15-25% on maintenance costs. They also improve decision-making by 40% and reduce energy use by 15%. Yet, 70% of projects face cybersecurity risks, and 55% struggle with system integration. The market is growing fast, expected to reach $139.3 billion by 2030, with 89% of large factories adopting digital twins by 2025. In conclusion, digital twins offer great benefits for factories, like cost savings and better planning. The survey shows 76.9% agree they improve decision-making, and 69.2% are ready to scale them. To succeed, factories must address challenges like cybersecurity, integration, and staff training. Future research should focus on small factories and improving data accuracy. Digital twins are a powerful tool for smart manufacturing, driving efficiency in Industry 4.0.

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