Vol. 08, No. 02, July 2024, pp. 1-10

INTERNATIONAL JOURNAL OF INNOVATION IN ENTERPRISE SYSTEM

Journal homepage: https://ijies.sie.telkomuniversity.ac.id
e-ISSN: 2580-3050, DOI: https://doi.org/10.25124/ijies.v8i02.269

Analyzing Digital Twin Adoption in Aluminum Plants Using Technology Readiness Index 2.0

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ARTICLE INFO

Article history:
Received 13 December 2023
Accepted 17 May 2024
Published 31 July 2024

ABSTRACT IN ENGLISH

In the era of industrial digitalization, Digital Twin technology offers a potential solution to enhance efficiency and innovation. This study investigates the readiness of workers in an Indonesian aluminum casting plant to embrace new technology, considering their perceptions of optimism, innovation, discomfort, and insecurity. A semi-quantitative approach was employed, utilizing the Technology Readiness Index (TRI) 2.0. The research involved four representatives selected by the industry's leadership. Questions were specifically designed to assess the readiness for Digital Twin technology in the aluminum casting plant. The data were analyzed using content analysis to determine the overall readiness for new technology and the characteristics of key personnel for Digital Twin technology. The overall Technology Readiness Index (TRI) 2.0 score indicated a grand mean of 3.75 (SD: 0.74), suggesting that the employees generally tend to be skeptical but slightly inclined towards a positive attitude in accepting Digital Twin technology for implementation in the aluminum casting plant.

Keywords:
Digital Twin, Technology Readiness Index (TRI) 2, Semi-quantitative Approach, Personnel Characteristics, Alumunium Casting Plant.

1. INTRODUCTION

Digital twin technology, rapidly advancing in industrial manufacturing, offers transformative benefits across various sectors. This concept entails creating a virtual replica of a physical entity, precisely mirroring its behavior and characteristics [1]. By leveraging real-time data, digital twin technology enables manufacturers to enhance and optimize production processes, resulting in cost savings and improved efficiency [2]. Digital twin has demonstrated profound potential in minimizing downtime, and improving overall productivity [3].

Digitalization is posited as a potential solution to a multitude of challenges, encompassing issues such as reliance on conventional equipment, the practice of recording operational data via manual logbooks, and the absence of system integration within the manufacturing environment [4]. Additionally, the expansive layout of factories necessitates considerable efforts in monitoring and data acquisition [5].

Digital twin technology is not just a tool for enhancing existing processes, it's a catalyst for innovation. For example, in predictive maintenance, digital twin can forecast equipment failures before they occur, allowing for timely repairs and avoiding costly downtime [6]. This proactive approach contrasts sharply with traditional reactive maintenance strategies. Moreover, the technology's ability to simulate different scenarios enables manufacturers to test and optimize machine settings or operational strategies in a virtual environment, saving time and resources that would otherwise be spent on trial-and-error in the real world [7].

The integration of digital twin technology also paves the way for more sustainable manufacturing practices. By accurately modeling energy consumption and waste production, manufacturers can identify areas for improvement and implement more eco-friendly processes [7]. This not only helps companies meet increasing regulatory demands but also appeals to the growing market of environmentally conscious consumers. Additionally, digital twin can assist in optimizing supply chain logistics, reducing the carbon footprint associated with transportation and storage of materials [8]. The implications of these advancements extend beyond mere compliance; they signify a shift towards a more responsible and sustainable industrial future.

Conversely, a number of scholarly critiques [9][10], highlight inherent limitations in the adoption of digital twin technology. A predominant concern centers on the potential overdependence on sophisticated digital modeling. This overreliance poses a risk of detachment from tangible physical processes and systems, as observed in various studies. Furthermore, in certain instances, these digital representations may fail to encapsulate the full complexity and nuances of the real-world environment. Such discrepancies can lead to decision-making and optimization strategies grounded in simulations that are not entirely congruent with actual scenarios, thereby compromising the efficacy and reliability of the outcomes.

Furthermore, the financial implications of integrating digital twin technology into manufacturing processes are significant [11]. The initial investment encompasses not only the cost of software and hardware but also the expenses involved in integrating these systems with existing infrastructure. This integration often requires specialized expertise and could entail additional costs for consulting and system customization. Moreover, the ongoing maintenance of digital twin systems presents its own set of financial challenges. These challenges include regular software updates, system monitoring, and the potential need for technical support, all of which contribute to the total cost of ownership. For smaller manufacturers or those with constrained budgets, these expenses can be daunting. The high upfront investment, coupled with ongoing operational costs, may render the adoption of digital twin technology a less viable option for these entities.

There are also significant concerns about data security and privacy. Given the heavy reliance of digital twin technology on real-time data acquisition and analysis, there is an increased vulnerability to cyber threats and potential breaches [12]. Consequently, safeguarding sensitive operational and production data becomes a paramount concern when integrating digital twin technology into manufacturing processes.

Lastly, the learning curve for employees and technicians to fully grasp and effectively utilize digital twin technology can be steep [13]. This may pose challenges in workforce training and adaptation, potentially leading to resistance to change and a slower transition to digital twin-enabled processes. Therefore, it is important for manufacturers to carefully weigh the potential challenges against these valid concerns when considering the adoption of digital twin technology.

In Indonesia's aluminum casting industry, the readiness to adopt this technology is vital, influenced by factors such as technological infrastructure, organizational culture, and perceived benefits [14]. A robust technological infrastructure, including high-speed internet, advanced computing systems, and secure data storage, is crucial for successful implementation.

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Digitalization is being vigorously pursued by the Indonesian government as a key strategy to enhance the performance of State-Owned Enterprises [15], [16]. This initiative has impacted various companies, including an aluminum casting plant (Figure1), which is undergoing transformation to integrate digital technologies into its manufacturing processes. A pilot project, launched in partnership with a private university, began in November 2023. The objective of this project is to implement digital twin technology in the aluminum casting plant.

Figure 1 - The Aluminum casting plant in real world

The digital twin dashboard is a visual representation of the real-world aluminum casting plant (Figure 2). It enables real-time monitoring of the factory from any location, provided there is an internet connection [17]. In addition to monitoring, this dashboard also collects data from sensors installed in the aluminum casting facility, thus facilitating rapid decision-making.

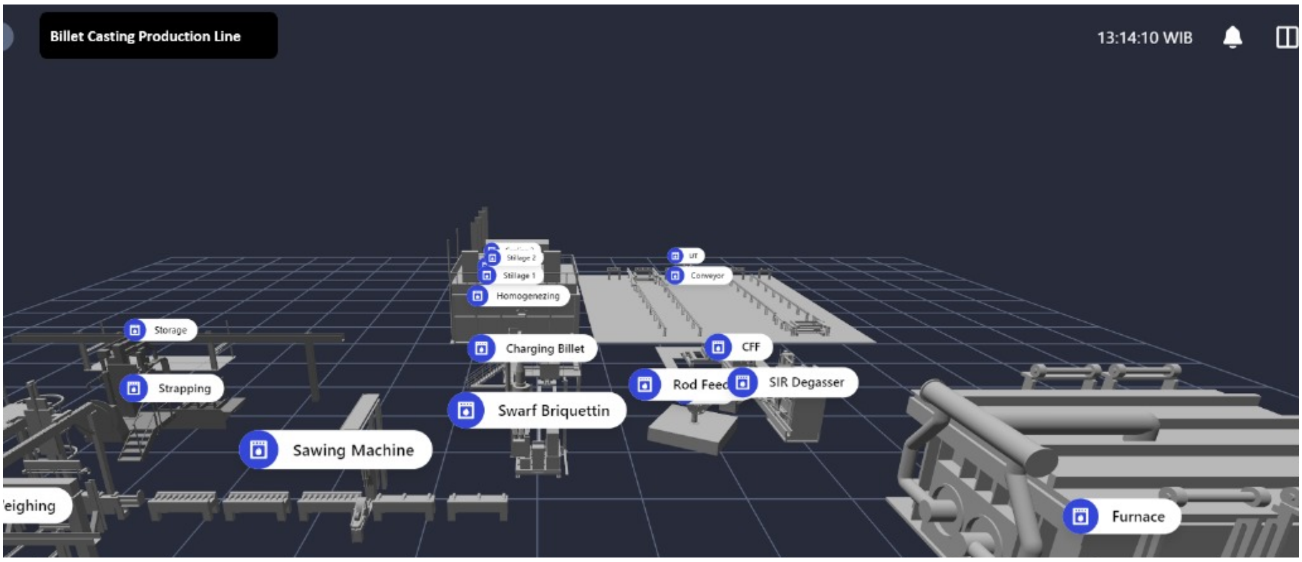

Figure 2 - The dashboard of digital twin technology in the aluminum casting plant

Based on observations in the aluminum casting plant, the implementation of the digital twin remains incomplete and faces several challenges. These include unidentified tag names in a Programmable Logic Controller (PLC), which hinder data collection. Additionally, vendor-protected PLCs prevent interconnectivity with other PLCs, making the digital twin implementation more difficult.

The implementation of digital twin technology in the aluminum casting plant faces numerous challenges, triggering diverse emotional responses among stakeholders, ranging from discomfort and insecurity to optimism about its rapid adoption in aluminum casting. This situation underscores the importance of research into personnel readiness for new technological adaptations.

It is evident that the challenges faced in implementing the digital twin in aluminum casting extend beyond technical issues. There are underlying complexities in the interplay of various systems and the readiness of personnel to embrace technological advancements. Understanding these challenges requires a comprehensive analysis of human factors, particularly personal readiness, which can influence the successful deployment of digital twin technology.

It is imperative to conduct in-depth research into personnel readiness for technological adaptations. By delving deeper into the underlying factors that influence the implementation of the digital twin, a more comprehensive strategy can be devised to navigate the complexities and pave the way for successful integration.

The Technology Readiness Index (TRI) 2.0 is a tool for assessing technology readiness levels within various groups, such as countries, demographic groups, professions, or market segments [18]. TRI 2.0 helps in understanding the dynamics behind the adoption of technologies by providing measures of the four technology readiness dimensions as well as overall technology readiness. TRI 2.0 has proven to be a robust predictor of technology-related behavioral intentions and actual behaviors. Additionally, it can serve as a moderating variable in multivariate framework studies.

Technology readiness is defined as a mental state that influences an individual's inclination to adopt new technologies. This concept is complex and consists of four dimensions: optimism, innovativeness, discomfort, and insecurity [18]. Optimism involves having a positive attitude toward technology and believing it enhances control, flexibility, and efficiency in life. Innovativeness describes a propensity to be an early adopter and leader in technological advancements. Discomfort is characterized by feelings of being overwhelmed and a perceived lack of control over technology. Insecurity reflects a distrust of technology, driven by doubts about its reliability and fears of its potential negative impacts.

The Technology Readiness Index (TRI) is valuable information in decision-oriented research where technology-based innovation is key [19]. TRI 2.0 can be utilized to categorize consumers into groups with varying levels of technology readiness, offering a unique perspective on the role of technology beliefs [20].

2. METHOD

This study employed a semi-quantitative method, utilizing the TRI 2.0 questionnaire, which encompasses four factors: Optimism, Innovativeness, Discomfort, and Insecurity. The factors of Optimism and Innovativeness are considered motivating dimensions that drive the adoption of new technologies. In contrast, Discomfort and Insecurity are inhibiting dimensions that can impede technology adoption [18].

A survey was conducted in aluminum casting plants (Figure 3), involving questionnaire responses from four key individuals: a supervisor, plant managers, a senior vice president, and representatives chosen by industry leadership. These four individuals were identified as key personnel due to their knowledge about the technologies used by the company.

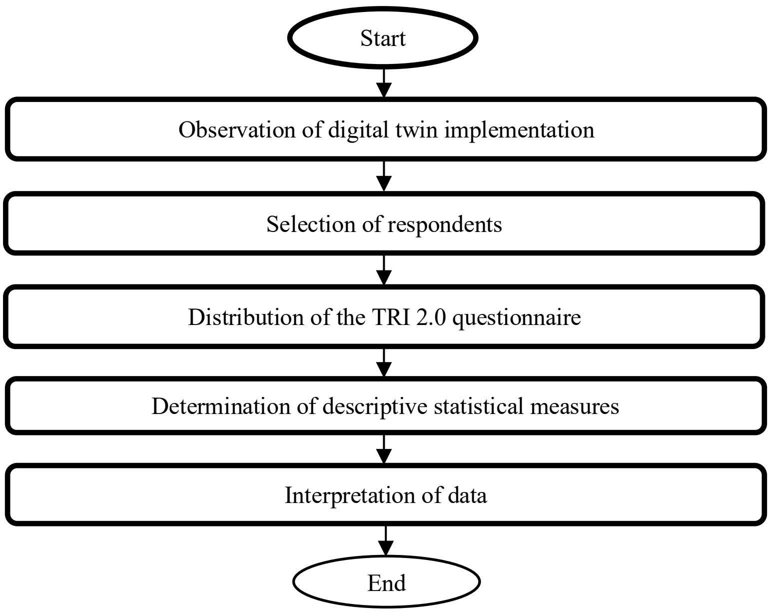

Figure 3 – Survey Methodology Using Technology Readiness Index (TRI) 2.0

The data is processed to ascertain the statistical descriptions of the measurement dimensions, such as mean values, minimum, and maximum. The mean values for these measurement dimensions are depicted in a radar chart. Subsequently, the grand mean and standard deviation values for the four dimensions are calculated. Finally, data interpretation will be conducted to determine worker segmentation in terms of their acceptance of new technology. The data processing used procedures derived from the TRI 2.0 [18].

Figure 4 - The mean values of the TRI 2.0 dimensions

3. RESULT

This study is designed to assess the level of readiness for adopting new technology within the aluminum casting industry. To achieve this, the methodology involves distributing the Technology Readiness Index (TRI) 2.0 questionnaire to employees who are directly responsible for overseeing and implementing technology within the plant. The subsequent passage will detail the results derived from this study.

Mean values reveal that almost all measured variables demonstrate a tendency towards positive emotional responses, with the notable exception of the Discomfort dimension (Figure 4). A mean optimism score of 4.75 suggests that the respondents have a positive view of technology and believe that it offers people increased control, flexibility, and efficiency in their lives. The mean Innovativeness score of 3.81, being close to neutral, suggests a tendency to agree with being a technology pioneer. A discomfort score of 3 implies a neutral attitude towards technology that is difficult to control and might be overwhelming. The insecurity score of 3.44 indicates a skeptical view that digital twin technology will work properly in the casting plant and concerns about its potential harmful consequences, yet there is a tendency to be open to accepting the risks associated with this insecurity. Understanding the grand mean score with TRI 2.0 is essential to identify the respondents' overall perceptions of the new technology, specifically digital twin (Table 1).

Table 1 - Recapitulation Statistics for Technology Readiness Index (TRI) 2.0

	Optimism	Innovativeness	Discomfort*	Insecurity*
Mean	4.75	3.81	3	3.44
Min	4	2.75	1.75	2.50
Max	5	5	4	4
Grand mean (SD)		3.75 (0.74)		

* The values have already been converted for the purpose of calculating the grand mean. High values indicate a low degree of resistance to implementing new technology. Conversely, low values suggest a low degree of motivation to implement new technology.

A score of 3.75 indicates that, in general, the respondents representing the company's employees tend to have a neutral stance but lean slightly towards a positive attitude in accepting Digital Twin as a new technology to be implemented in an aluminum casting plant. Furthermore, the standard deviation value of 0.74 provides insights into the degree of variation in responses among the respondents.

The data reflects a set of ratings across four categories, each with its mean, minimum, and maximum values. These metrics offer valuable insights into the respondents' perceptions within these distinct domains. In the first dimension (optimism), characterized by a high mean of 4.75, there is a notable consensus, with most respondents providing ratings close to the maximum score of 5. This suggests a remarkably positive sentiment or agreement within this category.

Moving to the second dimension (innovativeness) with a mean of 3.81, the responses exhibit a moderately positive sentiment. However, the wider range from a minimum of 2.75 to a maximum of 5 indicates a greater variability among respondents. This variability is even more pronounced in the third dimension (discomfort), where the mean of 3 suggests a neutral to slightly positive sentiment. The range from 1.75 to 4 underscores the diverse nature of responses, with some respondents expressing lower satisfaction.

In the fourth dimension (insecurity), with a mean of 3.44, there is a moderate to positive sentiment. The range of responses, spanning from 2.50 to 4, suggests a moderate level of variability. The grand mean of 3.75 provides an overarching average across all categories, and the standard deviation of 0.74 signifies the extent of variability around this mean. The coefficient of variation, calculated at approximately 19.73%, indicates a moderate level of relative variability in the dataset.

The Coefficient of Variation (CV) is a statistical measure that quantifies the relative variability of a dataset in relation to its mean. It is expressed as a percentage and is particularly useful for comparing the variability of datasets with different units or scales [21]. The formula for calculating the CV is:

$$CV = \frac{\sigma}{x}\ x\ 100\% \tag{1}$$

Calculation of CV for the TRI 2.0 dimensions:

$$CV_1 = \left(\frac{0.74}{4.74}\right) x\ 100\% = 15.58\% \tag{2}$$

$$CV_2 = \left(\frac{0.74}{3.81}\right) x\ 100\% = 19.42\% \tag{3}$$

$$CV_3 = \left(\frac{0.74}{3}\right) x\ 100\% = 24.67\% \tag{4}$$

$$CV_4 = \left(\frac{0.74}{3.44}\right) x\ 100\% = 21.51\% \tag{5}$$

Analyzing the Coefficient of Variation (CV) values for each dimension in column (see Table 1) provides valuable insights into the variability and consistency within specific categories. The CV, calculated as the ratio of the standard deviation to the mean multiplied by 100, serves as a relative measure, allowing for comparisons across different scales. In this context, we will explore the interpretation of CV values for Columns 1 through 4, shedding light on the implications of these metrics and how they guide a deeper understanding of the underlying data.

Starting with first dimension (optimism), the calculated CV of approximately 15.58% indicates a relatively low level of variability compared to the mean. This suggests that the responses or measurements in this category are clustered closely around the mean value of 4.75. The narrow spread of data points implies a high level of agreement or satisfaction, with respondents consistently providing ratings close to the average. This could indicate a robust consensus or uniformity of sentiment within Column 1, potentially pointing towards a positive and stable trend.

Moving on to the second dimension (innovativeness), where the CV is approximately 19.42%, we observe a moderate level of variability relative to the mean of 3.81. This suggests that while the average satisfaction in this category is moderate, there is a discernible degree of variability among responses. Some respondents may express more positive sentiments, contributing to the higher end of the range, while others might provide lower ratings, introducing a level of diversity in opinions or experiences. This moderate variability indicates a more nuanced landscape within Column 2, warranting a closer examination of specific data points to understand the contributing factors.

In the third dimension (discomfort), the CV of about 24.67% suggests a higher level of variability compared to the mean of 3. The wider spread of data points implies a range of opinions or experiences within this category. The mean being closer to the lower end of the scale indicates a neutral to slightly positive sentiment on average. However, the higher CV highlights that this category is characterized by a diverse set of responses, potentially reflecting a broader array of perspectives or factors influencing satisfaction. Further investigation into specific data points and potential outliers is crucial to unravel the nuances within Column 3.

In the fourth dimension (insecurity), the calculated CV is approximately 21.51%, indicating a moderate level of variability relative to the mean of 3.44. Similar to Column 2, this suggests that while the average satisfaction is moderate, there is a notable degree of variability among responses. Some respondents may provide higher ratings, contributing to the upper end of the range, while others express lower satisfaction, introducing diversity. This moderate variability hints at a mixed landscape within Column 4, prompting a closer examination of specific data points to identify patterns or trends.

4. DISCUSSION

Digitalization is a program actively promoted by the Indonesian government as part of its effort to enhance the quality of State-Owned Enterprises. One of the companies affected by this initiative, to transform and implement digitalization in its production process, is an aluminum casting plant. A pilot project has been launched in collaboration with a private university, which began in November 2023.

The success of implementing new technology depends not only on the availability of capital and equipment but also on the readiness of the human resources working at the plant [22]. Humans, as the primary agents in the production system, play a significant role in the successful technological transformation [23]. Therefore, the readiness of the workers is an interesting subject for research.

Data from the TRI 2.0 can be further analyzed by categorizing positive and negative emotions (Table 2). Subsequently, classification of characteristics can be conducted based on the values of these emotions [18]. 'Skeptics' often maintain a neutral stance towards technology, harboring neither overly positive nor negative emotions. 'Explorers' typically exhibit strong motivation (positive emotion) and minimal opposition (negative emotion). 'Avoiders' are characterized by significant opposition and little motivation. 'Pioneers' possess intense positive and negative emotions towards technology. 'Hesitators' are marked by their minimal level of innovativeness.

Table 2 - Worker Segmentation Regarding Acceptance of New Technology

Positive emotion	Negative emotion*	Segment
5.00	4.00	Explorer
3.50	3.88	skeptics
3.88	2.13	skeptics
4.75	2.88	Pioners

*High scores indicate a low degree of negative emotion. Low scores indicate a high degree of negative emotion.

Based on the results of this study, 50% of respondents are skeptical, with a slight tendency to be open to accepting Digital Twin technology. One individual is identified as an explorer, characterized by a strong desire to accept new technology and minimal resistance. Such workers are typically creative and drive continuous improvement. Additionally, another individual is a pioneer, motivated to embrace new technology but cautious about the significant risks associated with this technological transformation.

The majority of workers exhibit skepticism towards digital twin technology, but this is balanced by the presence of motivated individuals, including the explorer and the pioneer, in the aluminum casting plant. Moreover, it is highly feasible that these skeptical attitudes could shift towards positivity, provided that individuals' understanding is enhanced and they perceive tangible benefits from the advent of digital twin technology.

To foster greater optimism towards digital twin technology, it is crucial to enhance individuals' understanding and demonstrate its tangible benefits. This objective can be achieved through effective communication and training programs that emphasize the technology's positive impact on productivity, efficiency, and decision-making in aluminum casting [24], [25]. Additionally, involving employees in the implementation process and actively seeking their feedback can alleviate concerns or skepticism [1]. Engaging employees in this way ensures that their perspectives are considered and addressed.

Highlighting success stories and case studies from industries that have successfully adopted digital twin technology can help foster a more optimistic mindset [26]. These success stories can serve as powerful examples and inspiration for individuals at the aluminum casting plant, showing them the potential benefits and advantages of embracing this technology. The multiplying effect of embracing new technology can also be emphasized, showcasing how adopting digital twin technology can create a ripple effect of positive change throughout the industry [11]. Real-world examples demonstrating how digital twin technology has improved processes and outcomes in similar manufacturing settings can illustrate its potential benefits and alleviate any doubts about its efficacy.

To further enhance readiness for digital twin technology within the aluminum casting plant, it is crucial to foster a more innovative mindset. Such a shift necessitates the establishment of a culture that values learning and experimentation [27]. This goal can be achieved through targeted training programs, workshops, and knowledge-sharing sessions focused on digital twin technology. By creating opportunities for employees to actively engage in experimenting with digital twin applications and exploring their potential, a sense of curiosity can be ignited, thereby driving innovation.

Reducing discomfort during the adoption of digital twin technology requires several strategies. Firstly, comprehensive training and education on this technology can help alleviate any discomfort [28]. Workshops, seminars, and hands-on tutorials can familiarize employees with its features and functionalities. This approach empowers them to effectively understand and utilize the technology, contributing to a smoother transition and reduced apprehension.

Furthermore, creating a supportive and collaborative environment where employees feel comfortable asking questions and seeking assistance can also reduce discomfort [28]. Facilitating open communication channels and establishing regular feedback loops are essential to address any concerns or challenges related to digital twin technology. This approach will foster a sense of trust and encourage employees to embrace the technology with confidence.

To reduce insecurity regarding the adoption of digital twin as a new technology, it is vital to address the specific concerns and uncertainties employees may have. This can be achieved through open forums or focus group discussions, where individuals can express their apprehensions and receive clarifications from experts in digital twin technology. Directly engaging with employees and addressing their insecurities allows the organization to foster a sense of reassurance and transparency, leading to a smoother transition in accepting and embracing digital twin technology [3].

Highlighting the potential for career growth and professional development that comes with understanding and working with digital twin technology can also alleviate insecurity [29]. Emphasizing the value of acquiring new skills and knowledge in the technological landscape can inspire employees to view digital twin technology as an opportunity for personal and professional advancement.

Furthermore, establishing a mentorship or peer support system within the organization can offer employees guidance and assistance as they navigate the complexities of digital twin technology [3]. Pairing individuals experienced in digital twin applications with those less familiar can foster a collaborative learning environment, promoting knowledge exchange and skill development.

By addressing specific concerns, emphasizing professional growth opportunities, providing mentorship, and nurturing adaptability, workers can effectively minimize insecurity and cultivate a positive attitude towards integrating digital twin technology [27]. This holistic approach can pave the way for a successful and seamless implementation of digital twin technology in the manufacturing processes.

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5. CONCLUSION

Indonesia's aluminum casting sector is poised for significant gains through the adoption of digital twin technology. Despite challenges, the right strategies can fully harness this technology's potential for innovation and operational efficiency. The research findings suggest that the readiness of human resources towards new technology, specifically digital twin, is quite favorable. Workers generally tend to accept the introduction of new technology with positive emotions. Therefore, human resource readiness is not a significant obstacle for the implementation of digital twin technology.

Based on the results, a score of 3.75 indicates that the respondents, representing the company's employees, generally have a neutral stance but show a slight inclination towards a positive attitude regarding the acceptance of Digital Twin technology. This score suggests that while the employees are not overwhelmingly enthusiastic, they are open to the potential benefits and improvements that this technology could bring to the aluminum casting plant.

Based on these findings, it is clear that the readiness of human resources in the aluminum casting sector for digital twin technology is promising. The presence of motivated individuals, such as explorers and pioneers, indicates a positive potential for the acceptance and integration of this innovative technology. However, the skepticism among the majority of workers points to a need for focused efforts to enhance understanding and showcase tangible benefits.

To facilitate a shift towards greater optimism, prioritizing effective communication and training programs is imperative. These programs should emphasize the positive impact of digital twin technology on productivity, efficiency, and decision-making in aluminum casting. Involving employees in the implementation process and actively seeking their feedback can address concerns and skepticism, fostering a sense of ownership and engagement.

Highlighting success stories and case studies from other industries that have benefited from digital twin technology can serve as compelling examples to inspire and motivate workers. Additionally, creating a culture that values learning and experimentation through targeted training programs and knowledge-sharing sessions can spark a spirit of innovation among employees.

Addressing specific concerns and insecurities through open forums, and emphasizing potential career growth opportunities linked to digital twin technology, can help reduce skepticism and encourage a positive attitude towards its integration. Furthermore, pairing experienced individuals in digital twin applications with those less familiar can create a collaborative learning environment, promoting knowledge exchange and skill development.

In conclusion, while challenges do exist, the readiness of human resources in the aluminum casting sector for digital twin technology is not a major obstacle. By strategically focusing on enhancing understanding, showcasing tangible benefits, and fostering an innovative and supportive culture, the successful integration of digital twin technology in manufacturing processes is achievable. This comprehensive approach has the potential to unlock significant gains in innovation and operational efficiency for Indonesia's aluminum casting sector.

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