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IDENTIFYING THE TYPES OF FUTURE SKILLS NEEDED IN THE MANUFACTURING INDUSTRY: A SYSTEMATIC LITERATURE REVIEW

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Abstract:

Background: The advent of Industrial Revolution 4.0 has led to the need to redesign the jobs and skills required across various industries and markets. As the manufacturing industry has the most significant contribution to GDP, it has not escaped the impact of this revolution. The dynamics of industrial growth, which tend to fluctuate from year to year, are also significant indicators of the need for strategic efforts to enhance the sector's resilience and competitiveness. One step that can be taken is to identify the types of future skills required and relevant to the manufacturing industry to adapt to a changing environment.
Purpose: This study aims to identify the types of future skills needed by the manufacturing industry through a systematic literature review approach in order to obtain a comprehensive overview of relevant and strategic skill trends.
Design/methodology/approach: This research employed the Systematic Literature Review (SLR) method, adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. SLR serves as a systematic approach to identifying, evaluating, and synthesizing relevant previous research results, thereby obtaining a comprehensive understanding of the future skills required in the manufacturing industry. In addition, thematic analysis was used to identify and interpret patterns or themes within a dataset, as well as to develop a conceptual model of the study's results.
Findings/Results: 63 types of future skills were categorized into eight categories. The classification of future skills in this study consists of: 1) Interpersonal Skills, 2) Leadership and Management, 3) adaptive and resilient mindsets, 4) Higher-Order Thinking Skills, 5) Entrepreneurial and Business Skills, 6) Learning and Development; Social and Ethical Responsibility; and 8) Personal Effectiveness.
Conclusion: This research highlights the importance of the manufacturing industry in adapting to the changing demands brought about by Industrial Revolution 4.0 through the development of future skills. This study identified 63 types of future skills. It classifies them into eight main categories, considering the similarity of concepts, interrelationships in their application in the workplace, and the role of each skill in supporting individual readiness to face future challenges.
Originality/value: This study has substantial originality value because it fills a significant research gap related to future skills in the manufacturing industry context. The lack of previous studies that specifically address future skill needs in this sector indicates the need for further exploration to strengthen the scientific foundation while making practical contributions. Therefore, this study is the first step in identifying the types of future skills that are relevant and potentially applicable to the manufacturing industry in Indonesia.

Keywords: future skills, manufacturing industry, soft skills, systematic literature review, thematic analysis

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INTRODUCTION

The advent of the Fourth Industrial Revolution, commonly referred to as Industry 4.0, has necessitated the redesign of jobs and the skills required across various industries and markets (Sheikh et al. 2023). This has also led to long-term concerns about massive job losses worldwide (Willcocks, 2024). Although some jobs in Indonesia could potentially be replaced by automation, McKinsey and Company (2019) predicted that more new jobs will emerge in Indonesia by 2030. Approximately 23 million jobs in Indonesia could be replaced by automation, but approximately 27-46 million new jobs will also be created during this period. Additionally, approximately 10 million of the estimated jobs are new positions that did not exist previously (McKinsey & Company, 2019).

The COVID-19 pandemic is also cited as a catalyst for advanced technologies that will propel the world into the future (Gouda, 2022). Survey results from McKinsey and Company (2020) show that Covid-19 has accelerated the digitization process in various sectors, especially in terms of remote work, asset migration to the cloud, data security, adjustment to changing customer expectations, demand for online purchases and services, and the use of more advanced technology in business operations and decision-making. Sheikh et al. (2023) also mentioned COVID-19 as one of the factors that had a significant impact on the need to redesign jobs and skills in all industries and markets. The primary challenge to overcome in an era of continuous change is identifying the skills required and providing a competitive advantage for employees in the future (Skrzek-Lubasinska & Malik, 2023). In addition, the ever-changing environment puts enormous pressure on the business world, resulting in a growing need for individuals and companies to master new skills and adapt to future challenges. This is certainly not easy, considering that an uncertain and unstable business environment leads to judgments that are often short-lived or temporary (Willcocks, 2024). To effectively project future demands and priorities, we must focus on developing flexible and transferable skills (Vista, 2020).

In line with the views of Skrzek-Lubasinska and Malik (2023), who emphasize the importance of identifying future skills in facing a dynamic and uncertain business environment, the Indonesian manufacturing industry needs to take the initiative to anticipate and adjust to future competency needs. Therefore, this study is conducted to identify the future skills required by the manufacturing industry through a systematic literature review, aiming to provide an overview of relevant and strategic skills trends. Through this approach, this research will collect, evaluate, and synthesize findings from various previous studies that address future skill needs, especially in the manufacturing industry.

Future skills generally refer to knowledge, attitudes, values, skills, and competencies designed to equip individuals to adapt and survive in an uncertain future (Kotsiou, 2022). Various entities involved in strategic decision making in education, including non-profit, semi-public, and government organizations, have attempted to identify the skills most needed in the future. However, these efforts have resulted in various frameworks that often lack consensus with different definitions and identification of future skills. Many of these frameworks propose hundreds of skills, making it challenging to obtain a more comprehensive overview of current thinking (Kotsiou, 2022). This suggests an increasing need for further academic synthesis to combine fragmented perspectives and provide a structured and context-relevant classification of future skills, particularly in the manufacturing sector. Therefore, this study contributes to the existing body of knowledge by providing a systematic review and thematic analysis that fills gaps in previous research.

According to Vista (2020), skill assessment is highly dependent on the characteristics of each field in a job group. Therefore, Indonesia’s manufacturing industry was chosen as the object of this study because it exhibits dynamic job characteristics and is highly influenced by technological development and automation. Additionally, the manufacturing industry is a strategic sector that makes the most significant contribution to Indonesia’s gross domestic product (GDP), as shown in Table 1. The manufacturing industry makes the most significant contribution to gross domestic product (GDP) at current prices in 2024. The contribution made was 19.74% or equivalent to 4,202,867 billion rupiah. This indicates that the manufacturing industry is not only the primary driver of national economic growth but also plays a crucial role in creating jobs in Indonesia. Nevertheless, the growth of the manufacturing industry continues to exhibit a fluctuating pattern from year to year. This is illustrated in Figure 1.

Table 1. Gross domestic product at current prices in 2024

Business Field	Gross Domestic Product (Billion Rupiah)	Contribution to GDP (%)
Agriculture, Forestry, and Fishing	2,791,428	13.18
Mining and Quarrying	2,026,589	9.57
Manufacturing	4,202,867	19.84
Electricity and Gas	227,527	1.07
Water Supply; Sewerage, Waste Management, and Remediation Activities	14,259	0.07
Construction	2,233,463	10.54
Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	2,892,695	13.65
Transportation and Storage	1,358,117	6.41
Accommodation and Food Service Activities	584,447	2.76
Information and Communication	960,022	4.53
Financial and Insurance Activities	922,811	4.36
Real Estate Activities	520,728	2.46
Business Activities	424,170	2.00
Public Administration and Defence; Compulsory Social Security	673,718	3.18
Education	621,417	2.93
Human Health and Social Work Activities	278,216	1.31
Other Services Activities	454,309	2.14

Based on Figure 1, it can be seen that the manufacturing industry's contribution in 2020 reached its highest number, amounting to 20.62%. However, in 2021 and 2022, these rates decreased to 20.06% and 19.18%, respectively. This reflects pressure on the manufacturing sector, one of which is the COVID-19 pandemic. Starting in 2023, the contribution of the manufacturing industry began to show signs of recovery, with an increase of 19.52%, and continued to improve in 2024, reaching a contribution of 19.84%. Based on this trend, it was found that although the manufacturing industry is the most significant contributor to GDP, its growth is not always stable and is strongly influenced by external and internal dynamics. Therefore, strategic steps are necessary to strengthen the resilience and competitiveness of this industry, particularly through the development of human resources that can adapt to change.

This study employed the Systematic Literature Review (SLR) method, which is based on clearly formulated research questions and applies systematic and transparent procedures to identify, select, and critically assess relevant research, as well as collect and analyze data from studies included in the review (Moher et al. 2009). Through this approach, research is expected to identify future skills needed in the manufacturing industry.

METHODS

The data used were secondary data derived from various scientific studies relevant to the topic of study. However, only scientific journal articles that reached the final stage of publication were included as data sources.

The data collection technique employed a Systematic Literature Review (SLR) approach. The implementation of the systematic literature review method in this study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, as compiled by Moher et al. (2009) and illustrated in Figure 2.

Identification

The first step in a systematic literature review (SLR) using the PRISMA guidelines is to identify the literature through database screening. The criteria for the literature needed in this study are: 1) literature using English or Bahasa Indonesia; 2) literature published within the last 10 years (2015-2025) and can be accessed in its entirety; 3) literature that has reached the final stage of publication; 4) literature in the form of scientific articles; and 5) literature discussing future skills that focus on the manufacturing industry or skills that are general across sectors (but do not include specific sectors outside of both).

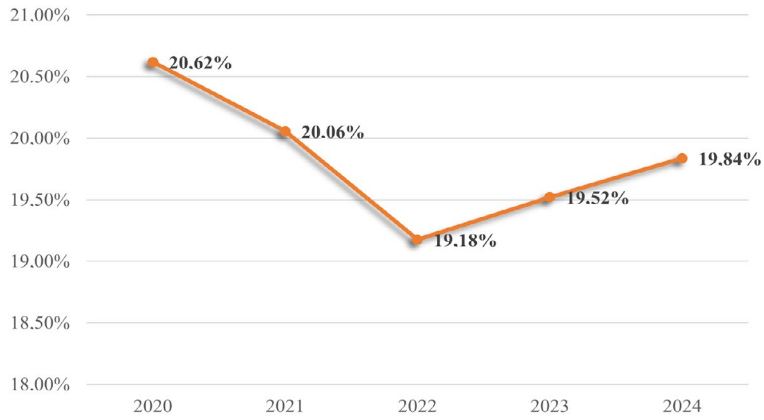

Figure 1. Contribution of the manufacturing industry to GDP

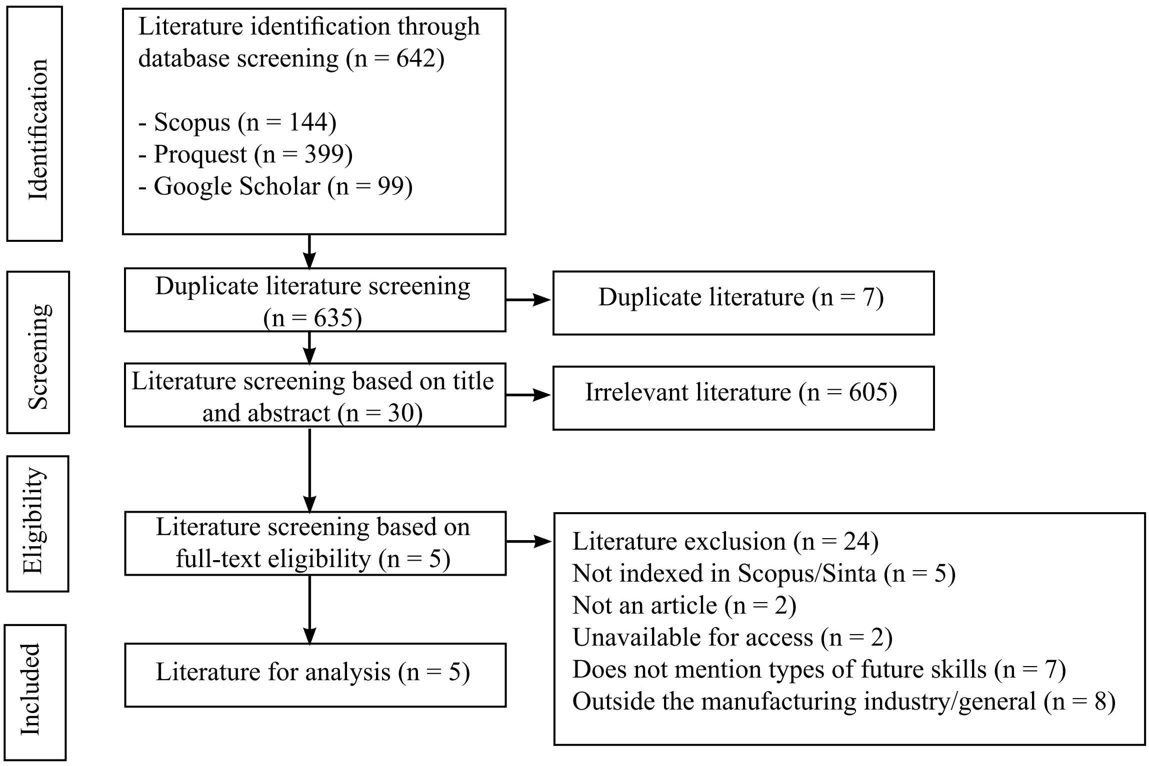

Figure 2. Flowchart PRISMA

The literature search focused on the titles, keywords, and abstracts to ensure that the references obtained were relevant to the research topic. The databases used to collect the literature in this study included Scopus, ProQuest, and Google Scholar. A total of 642 scientific articles were found based on the literature search and filtering.

Screening

After the literature identification process was completed, screening for duplicated literature continued, and seven instances of duplication were identified. After that, duplicates were removed, leaving 635 scientific articles. Next, literature screening was conducted based on the title and abstract. The title filtering process was performed using the keywords. If an article does not contain words that match the keywords, it will not be accepted. Meanwhile, abstract screening was performed by considering the following questions: Does the study focus on future skills?; Does the study discuss the types or framework of future skills in the manufacturing industry or its general scope?.

Articles that were categorized as accepted were those that answered "yes" to both questions. Articles that had a "no" answer to one or both questions were categorized as unsuccessful at this stage. The total number of articles that passed title and abstract screening was 30articles.

Eligibility

At this stage, literature was filtered based on full-text eligibility, where literature that was not indexed by Scopus/Sinta, not in the form of scientific articles (such as books, proceedings, theses, theses, news, reports, and other types of publications), no access to full text, not by the research objectives, and the scope of future skills outside the manufacturing industry or skills that can be applied in general throughout the industry were excluded from this study. At this stage, five studies that passed was 5.

Included

This stage describes the literature that was ultimately used in the analysis process. Five pieces of literature were analyzed in this study. This reflects the lack of research that explicitly discusses future skills in the manufacturing industry. This also highlights a significant research gap as well as the need to conduct further exploration to strengthen the scientific and practical basis for developing future skills in the manufacturing industry.

The collected data were analyzed using a thematic analysis. Thematic analysis is a research method used to identify and interpret patterns or themes within a dataset and develop conceptual models (Naeem et al. 2023). NVivo software was used to assist with the thematic analysis process. The choice of NVivo software is based on its ability to assist researchers in organizing, coding, and identifying patterns in data more systematically, thereby helping them identify the main themes more accurately.

This study adopts the thematic analysis stages proposed by Naeem et al. (2023), which consist of six stages. The following is an explanation of each stage.

Transcription, Familiarization with The Data, and Selection of Quotations

This was the first stage of the thematic analysis process, in which the researcher transcribed the data and delved deeply into the content to understand the initial themes and key aspects. The researcher then selected quotes that provided an overview of the research findings and represented various perspectives and patterns relevant to the research objectives. This stage involved reading in more detail the types of future skills identified in each of the articles studied. The types of future skills studied in this research were only those included in the soft skills category. This was done based on the consideration that soft skills are more flexible and can be applied to various divisions, unlike complex/technical skills, which often require specific skills according to the needs of certain divisions. In addition, soft skills can also be considered distinctive human skills that will remain valuable in the workplace (Willcocks, 2024).

The first article by Brasse et al. (2023) found as many as 10 future skills needed in the German manufacturing industry. The second article by Kotsiou et al. (2022) found 33 future skills that can be applied across industries. The third article by Bukartaite and Hooper (2023) identifies 32 future skills that can be applied across various industries. The fourth article, by Akyazi et al. (2022), identified 31 future skills required in the manufacturing industry. Finally, the fifth article by Babashahi et al. (2024) identified 11 future skills that can be applied across various industries.

Given the wide variety of future skills identified, it is important to conduct further in-depth research on these skills. The aim is to group and categorize future skills based on similarities in form or function to avoid duplication between the literature and to further filter them according to the research scope, which focuses entirely on identifying soft skills.

Selection of Keywords

At this stage, the researcher observes the patterns or terms that appear frequently and establishes them as keywords. For example, in the analysis of future skills of workers in the manufacturing industry, some of the keywords that emerged were “communication”, ”collaboration”, “lifelong learning”, “critical thinking”, “emotional intelligence”. These keywords can reflect future skills considered important in facing industrial transformation, and can serve as a basis for further analysis to identify the main themes of the research.

Coding

In the third stage, data segments containing the primary meaning are labeled using short phrases or words referred to as codes. In this study, the coding stage is also used to unify various terms or phrases that actually have the same meaning but are mentioned differently. This stage is crucial for preventing data duplication and for producing a more accurate and representative classification. At this stage, an initial total of 108 soft skills were identified from the five literature sources. After reviewing the coding process, 63 future skills relevant to the manufacturing industry were identified. Thus, this coding process succeeded in simplifying and eliminating overlaps between literature, as well as producing a more comprehensive list of future skills ready for further analysis.

Theme Development

This stage focuses on grouping the identified codes into more meaningful categories. The aim is to recognize the initial patterns or relationships between codes so that previously fragmented data can begin to show a specific structure. In this research, this stage was used to categorize the 63 types of future skills into eight primary classifications based on similar characteristics, functions, and relevance. This stage involves the initial organization, where researchers begin to form clusters or themes based on the coding results.

Conceptualization through Interpretation of Keywords, Codes, and Themes

This stage involved a more in-depth process of interpreting and formulating the main concepts that emerged from the theme development results. This stage is a process of abstraction and conceptualization, in which the researcher seeks to understand the essence of each theme and relate it to theoretical contexts or real practices. Additionally, the researcher sought to refine the definitions of each classification so that they could become applicable and relevant concepts for the needs of the manufacturing industry.

Development of Conceptual Model

This is the final stage in the thematic analysis process, which is used to compile a systematic and visual representation of the results of conceptualizing future skills that have been previously identified.

RESULTS

Summary of Selected Literature

The literature reviewed and used in this research was limited, as shown in Table 2. This is because of the lack of literature on the types of future skills required in the manufacturing industry. The majority of the literature discusses the future skills prevalent in the education sector, encompassing schools and universities. Given the significant contribution of the manufacturing industry to GDP and the lack of research specifically addressing the need for future skills in the Indonesian manufacturing industry, this study was conducted as a first step in identifying the types of future skills that are relevant and potentially applicable to the manufacturing industry in Indonesia.

The first article selected in this study was written by

Table 2. Selected Literature

Title	Author (Year)	Method
Preparing for The Future of Work: A Novel Data-Driven Approach for The Identification of Future Skills	Brasse et al. (2023)	Data-driven approach
A Scoping Review of Future Skills Frameworks	Kotsiou et al. (2022)	Thematic analysis & social network analysis
Automation, Artificial Intelligence, and Future Skills Needs: An Irish Perspective	Bukartaite and Hooper (2023)	In-depth interviews
Identifying Future Skill Requirements of the Job Profiles for a Sustainable European Manufacturing Industry 4.0	Akyazi et al. (2022)	Literature review & automated skills database development
AI in the Workplace: A Systematic Review of Skill Transformation in The Industry	Babashahi et al. (2024)	Systematic literature review

Brasse et al. (2023). The article discusses the rapid changes occurring in the world of work, driven by technological developments, decarbonization, and social upheaval, which necessitate employees acquiring new skills. Brasse et al. (2023) also attempted to identify future skills required in a case study of the German manufacturing industry. The results showed that 33 future skills are needed and valuable to support the country's manufacturing industry needs.

Kotsiou et al. (2022) explained that future skills encompass knowledge, attitudes, values, skills, and competencies that are designed to prepare students to face future challenges. Kotsiou et al. (2022) employed thematic and social network analyses to identify future skills required. Kotsiou et al. (2022) successfully identified nine meta-categories of future skills: 1) higher-order thinking skills, 2) dialogue skills, 3) digital and STEM literacy, 4) values, 5) self-management, 6) lifelong learning, 7) enterprise skills, 8) leadership, and 9) flexibility. The results can be used to provide an overview that can assist educational practitioners, human resource professionals, policymakers, and educational technology developers in integrating specific skills into learning and retraining. Therefore, the results of Kotsiou et al. (2022) can contribute to ensuring that students and the workforce are better prepared for a future filled with uncertainty.

Bukartaite and Hooper (2023) examined the views of key stakeholders on the skills required in the future as reliance on artificial intelligence (AI) and technology continues to increase. The research involved representatives from various organizations in Ireland, including both the public and private sectors. One of Bukartaite and Hooper's (2023) research findings also highlighted the importance of emphasizing and prioritizing lifelong learning.

Akyazi et al. (2022) examine how rapid digitalization and growing demand for sustainability are transforming the European manufacturing industry. The industry is undergoing significant transformation, requiring an effective strategy to address technological advancements and sustainability demands. One of the key factors shaping the success of such transformation is the development of a workforce with relevant skills. The outcome of Akyazi et al.'s (2022) research is an automated skills database for the manufacturing industry that encompasses not only current skills, but also future skills derived from in-depth literature research.

Finally, research conducted by Babashahi et al. (2024) discusses the transformative impact of artificial intelligence (AI) in various industries. Babashahi et al. (2024) reviewed 39 articles from the Scopus database and selected 20 relevant articles to review AI integration in business, identify critical skills, and analyze emerging challenges and solutions. A key finding of Babashahi et al. (2024) is that skills and adaptability are crucial for effective AI adoption.

Based on five literature reviews that have been further examined regarding the types of future skills relevant to the manufacturing industry, various types of future skills have been identified that can be adapted in this study. However, not all skill classifications from each literature review were used in their entirety. The selection was made selectively to ensure that the types of future skills adapted were truly relevant and appropriate for the research needs, particularly in the context of developing future soft skills in the Indonesian manufacturing industry. The types of future skills adapted from previous research are presented in Table 3.

Based on Table 3, 108 types of future skills relevant to this study were identified from five literature reviews. However, several types of skills, such as communication, leadership, and creativity, appear in more than one literature review. The repeated appearance of these skills indicates that they have been consistently considered important in several literature reviews. Therefore, further analysis is necessary to identify the relationships, commonalities, and potential overlaps between these skills. This analysis is crucial for preventing duplication in classification and ensuring that each identified skill has a clear definition and appropriate relevance within the context of the manufacturing industry needs.

Types and Classification of Future Skills

The findings obtained from the systematic literature review were further analyzed using thematic analysis. This approach aimed to identify patterns, classifications, and major themes related to future skills. In addition, thematic analysis helps avoid overlap between emerging skills so that each skill can be clearly defined and has its uniqueness. The types of future skills identified from the five selected literature sources through a systematic literature review totaled 108 types of future skills. After thematic analysis, 63 types of future skills were deemed relevant to the Indonesian manufacturing industry. The 63 types of future skills were then grouped based on similarities in their characteristics, functions, and roles. This process resulted in eight main classifications, making it easier to understand the structure of future skills in an organized and comprehensive manner. The following is an explanation of each classification of future skills that has been compiled.

Interpersonal Skills

This is a future skill classification that includes an individual's ability to communicate effectively, cooperate with others, and build positive interpersonal relationships. Communication and interpersonal skills are crucial for facing the challenges of automation (Babashahi et al. 2024). This is because the ability to interact effectively, negotiate, and build strong relationships with others can provide added value that is difficult to replicate using technology. In addition, successful collaboration is highly dependent on the quality of interpersonal relationships, which can be improved through positive communication (Mickel, 2024).

Leadership and Management

This classification encompasses the ability to lead, manage resources, make informed decisions, and direct individuals or organizations toward predetermined goals. According to Azad et al. (2017), leadership and management are not completely separate concepts, but rather complementary and fused in practice. This is because effective leadership cannot stand alone without elements of management, and vice versa.

Adaptive and Resilience Skills

This classification reflects an individual's ability to adapt to change, face challenges, and be resilient to dynamic and uncertain situations. Adaptability is key to responding quickly to technological developments, whereas a resilient resilient mindset can help individuals and teams overcome obstacles and uncertainties (Babashahi et al. 2024).

Table 3. Types of future skills adapted from the five literature sources

Type of Future Skills	Sources
Communication, customer orientation, creativity, flexibility, goal orientation, initiative, leadership, organization skills, problem solving, resilience	Brasse et al. (2023)
Decision making, problem solving, critical thinking, systems thinking, collaboration, communication, empathy, listening, ethical reasoning, citizenship, sustainability, global awareness, self-awareness, resilience, emotional intelligence, positive attitudes, confidence, learning to learn, metacognition, willingness to learn, active learning, creativity, initiative, entrepreneurship, curiosity, responsibility, goal-oriented, courage, management, adaptability, multi-tasking, agility, executive function	Kotsiou et al. (2022)
(People) management, creativity, communication, emotional intelligence, sales skills, influencing, trust building, storytelling, intrapreneurship, relationship management, business development, innovation, negotiation skills, co-creation, coaching, mental health support, proactivity, equality, diversity and inclusion, engaging others, adaptability, resilience, leadership (through uncertainty/ambiguity), flexibility, change management, abstract thinking, trainability, collaboration, critical thinking, decision-making, design thinking, lifelong learning agility, strategic problem-solving	Bukartaite dan Hooper (2023)
Problem solving, autonomy, critical thinking, coordination, continuous learning, teamwork, adaptability to change, entrepreneurship skills, business awareness, customer awareness, self-management, advanced communication skills, leadership skills, social responsibility, ethical responsibility, decision-making, people management, negotiation, opportunity assessment, common good, psychological and mental flexibility, cultural empathy	Akyazi et al. (2022)
Lifelong learning, adaptability, creativity, communication, emotional intelligence, decision-making, interpersonal skills, critical thinking, leadership skills, cognitive skills, social and emotional skills	Babashahi et al. (2024)

Higher-Order Thinking Skills

This classification includes the ability to think critically, analyze information, and structure solutions systematically and logically. These skills enable individuals to understand problems thoroughly, evaluate multiple perspectives, and make informed decisions based on data and structured thinking. Owing to automation, the demand for cognitive abilities will shift from basic skills to higher cognitive skills (Akyazi et al. 2022). Therefore, the workforce must develop these skills to remain relevant and competitive in the era of growing automation.

Entrepreneurial and Business Skills

This classification relates to the ability to identify opportunities and develop business strategies, as well as to understand customer needs to create value and generate profits. Entrepreneurs and aspiring entrepreneurs consider business management the most important factor in achieving success (Hatthakijphong & Ting, 2019). Understanding and implementing effective management strategies are key to building and running sustainable businesses.

Learning and Development

This classification is a future skill classification that reflects an individual's ability to continue learning and developing. Lifelong learning is considered a crucial attribute for individuals to continually adapt to evolving job demands (Kotsiou et al. 2022).

Social and Ethical Responsibility

This classification reflects individual awareness, responsibility, and commitment to the social, ethical, and sustainability aspects. The success and effectiveness of social responsibility strategies depend heavily on the participation of employees, who also play a strategic role in achieving overall business goals (Molnar et al. 2021).

Personal Effectiveness

This classification relates to an individual's ability to self-manage, build trust, and maintain mental wellbeing. Well-being reflects not only one's health, but also work and life as a whole (Schulte & Vainio, 2010). In addition, well-being can be referred to as a concept that describes the quality of work life and is a significant factor in determining the productivity of individuals, companies, and society as a whole.

Based on the eight previously defined classifications of future skills, a conceptual model was developed to describe the interrelationships between skills in a structured and integrative manner. This model aims to systematically map future skills while illustrating the cross-classification relationships that support one another. A visualization of the conceptual model is shown in Figure 3.

Figure 3 is a conceptual model that illustrates the classification and interconnectedness of future skills required in the manufacturing industry. Each classification in the model represents a complementary set of skills that do not stand alone but rather overlap with one another. For example, skills such as leadership, responsibility, and emotional intelligence appear in more than one classification because they have multiple roles in supporting personal effectiveness, interpersonal abilities, and strategic decision making. While the classifications were previously designed to minimize overlap between skills, thereby creating a more transparent and systematic mapping structure, the model was intentionally designed to illustrate how skills connect and contribute across classifications. Therefore, the model not only categorizes skills structurally but also provides a fuller understanding of the roles and relationships between skill dimensions, which is important in developing human resources that are ready to face the dynamics and complexity of the manufacturing industry in the future.

Managerial Implication

Theoretically, this research can contribute to the development of the literature related to future skills, specifically the category of soft skills required in the manufacturing industry. In addition, the use of the systematic literature review (SLR) methodology combined with the PRISMA approach demonstrates how the method can be effectively employed to screen and identify literature related to future skills required in the manufacturing industry. Although the SLR results were obtained from research conducted in various countries, the identified future skills remain relevant and can be applied in the Indonesian manufacturing industry. This is due to the increased adoption of technology, changes in industry trends resulting from globalization, and the need for an adaptable and competitive workforce in the international market. In addition, many Indonesian manufacturing companies are part of global supply chains, so the required skill standards also follow international developments; therefore, the findings of this study can still be stated as relevant and applicable in the Indonesian manufacturing industry. In addition, given the absence of research specifically discussing future skill needs in the Indonesian manufacturing industry, this study can be an important first step in opening up opportunities and broadening insights for future research.

Practically, the findings of this study can be utilized by individuals and the workforce to understand and develop relevant future skills, thereby increasing competitiveness in an increasingly competitive job market. In addition, the results of this study can serve as a reference for the manufacturing industry in designing training programs and developing workforce skills that are aligned with the industry's future needs and demands. Governments and policymakers can also utilize the findings of this study as a basis for formulating labor policies that are more adaptive to industrial changes. Therefore, this research not only contributes to the development of future skills theory, but also offers practical benefits that are useful for various stakeholders in responding to future industry challenges.

Figure 3. Conceptual model of future skills in manufacturing industry

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

Identifying future skills is important for responding to industry challenges and facing a dynamic and uncertain business environment. The absence of research specifically examining the needs related to future skills in Indonesia's manufacturing industry, which has the most significant contribution to national GDP, highlights the urgency to conduct further exploration to strengthen the scientific and practical basis for developing future skills in the manufacturing industry. The findings of this study identified 63 types of future skills and categorized them into eight classifications. The classification of future skills in this study consists of: 1) Interpersonal Skills; 2) Leadership and Management; 3) Adaptive and Resilience Skills; 4) Higher-Order Thinking Skills; 5) Entrepreneurial and Business Skills; 6) Learning and Development; 7) Social and Ethical Responsibility; and 8) Personal Effectiveness. These eight classifications were organized by considering the similarity of concepts, interrelationships in their application in the world of work, and the role of each skill in supporting individual readiness in facing future challenges. Based on this classification, a conceptual model was developed to describe the interrelationships between the skills in a structured and integrative manner. The model aims to systematically map future skills while illustrating the cross-classification relationships that support one another.

Recommendations

Although this study provides a comprehensive mapping of future skills, several limitations must be considered. Therefore, future research should conduct empirical validation to test the relevance of the identified skills. Empirical research can be conducted using surveys, interviews, or focus group discussions (FGDs) to explore the perspectives of practitioners and workers on the application of future skills in the Indonesian manufacturing industry. Further exploration of hard skills, as well as the combination of soft and hard skills, can be performed to provide a more holistic understanding of building workforce readiness in the future.

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