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## Article

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## Article

# The Impact of Knowledge Management and Organizational Learning Promotion in Small and Medium Enterprises on the Implementation of Industry 4.0 and Competitiveness

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**Abstract:** The transformation and upgrading of small- and medium-sized enterprises (SMEs) need to align with global industrial development trends and can further assist SMEs in sustainable operation. In recent years, major industrial countries, such as Germany, China, and the United States, have promoted policies like Industry 4.0 or advanced manufacturing as part of their national manufacturing transformation strategies. In contrast, how SMEs follow these global industrial development trends and effectively apply new technologies hinges on internal knowledge management and organizational learning. To achieve the benefits of new technology implementation, enterprises must establish an effective knowledge management and organizational learning mechanism and promotion practices. The Taiwanese government has also adopted Industry 4.0 as an essential tool for assisting the transformation and upgrading of SMEs. Therefore, this study surveyed 129 SMEs in the Taiwanese metal industry, using a one-way ANOVA, Pearson correlation analysis, and simple regression analysis to explore the impact of the internal promotion of knowledge management and organizational learning on the introduction of Industry 4.0 and the enhancement in competitiveness. The results of this study indicate that the promotion of knowledge management and organizational learning contributes to the effective adoption of Industry 4.0 and the enhancement in competitiveness, showing significant correlations between these factors. Thus, the findings can serve as a reference for other partner countries.

**Keywords:** knowledge management; organizational learning; Industry 4.0; sustainable operation; SMEs



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## 1. Research Background

### 1.1. Research Motivation

In today's fiercely competitive market, how small- and medium-sized enterprises (SMEs) can enhance their competitiveness to achieve sustainable development has become a primary task for government units worldwide in promoting industrial transformation and upgrading. Under the trend of global market supply chain reorganization and the development of Industry 4.0, organizational learning capabilities can significantly enhance the impact of Industry 4.0 on enterprise operational performance. Through systematically promoting learning and knowledge sharing, enterprises can achieve greater benefits in the implementation of Industry 4.0 technologies. Moreover, knowledge sharing is crucial for maintaining a long-term competitive advantage (Tortorella et al. 2020; Manesh et al. 2021). Additionally, (Li et al. 2019) pointed out that, under the context of Industry 4.0, the manufacturing industry faces increasingly complex challenges, and enterprises need to emphasize knowledge sharing and organizational learning to cope with growing market demands and competitive pressures. For SMEs, knowledge is one of the most valuable resources; through knowledge sharing, enterprises can effectively transmit internal expertise and

technical skills to all employees. This not only enhances individual employee capabilities but also fosters overall innovation within the enterprise. When every employee quickly grasps new technologies and knowledge, the enterprise is more likely to adapt to market changes and anticipate new challenges (Hussein et al. 2016). Furthermore, organizational learning plays a crucial role in SMEs; organizational learning is not merely the sum of individual learning by employees but also a manifestation of collective wisdom. Through organizational learning, enterprises can effectively integrate and exchange the wisdom and experiences of various departments and teams, thereby better responding to market changes and challenges. When a good learning mechanism and culture are established within the organization, the enterprise is more likely to gain a competitive advantage (Tu and Wu 2021). Thus, the introduction of Industry 4.0 technologies has a profound impact on the collaborative culture and knowledge-sharing mechanisms of enterprises, highlighting the importance of organizational learning and knowledge management in the era of Industry 4.0 (Lepore et al. 2021). Knowledge sharing and organizational learning are crucial pathways for SMEs to enhance their competitiveness. Through the effective application of these two elements, enterprises can better cope with market changes and improve their competitiveness.

### 1.2. Research Design

This study intends to collect knowledge management, organizational learning, Industry 4.0, and competitiveness through a literature review. The collected literature will serve as the foundation for this research, further exploring the impact of knowledge management and organizational learning on Industry 4.0 and competitiveness. The study will focus on the following research questions:

Investigate the impact of promoting knowledge management and organizational learning on Industry 4.0 in SMEs.

Explore the impact of promoting knowledge management and organizational learning on the competitiveness of SMEs.

Examine the impact of promoting Industry 4.0 on the competitiveness of SMEs.

## 2. Literature Review

### 2.1. Knowledge Management

In the digital era, knowledge sharing is regarded as a key factor in promoting innovation and enhancing the performance of R&D teams. Xiao et al. (2021) proposed an evolutionary game model for knowledge sharing in R&D teams based on evolutionary game theory, exploring the evolutionary path, stable strategies, and influencing mechanisms of knowledge sharing systems. The study pointed out that the cognitive abilities of members, knowledge absorption capacity, knowledge transformation ability, knowledge innovation ability, and the complementarity of knowledge within the team promote the effectiveness of knowledge sharing in R&D teams. On the other hand, in the era of digital transformation, knowledge management is crucial for handling a large amount of available information and must lead in the generation, sharing, use, and management of relevant knowledge and information. However, existing knowledge management measures may be insufficient to promote knowledge sharing among partners, focusing too much on unidirectional knowledge flow. Therefore, digital collaboration platforms enhance the potential for bidirectional knowledge sharing (Brouwers et al. 2022). Mihardjo et al. (2019) proposed an important viewpoint that knowledge sharing and transformational leadership styles can improve team performance. Additionally, the process of creativity often begins with knowledge sharing among team members, especially in the context of sharing tacit knowledge within a specific field. Through this knowledge sharing, teams can generate numerous novel ideas, driving successful outcomes such as new products, processes, and patents. Mayastinasari and Suseno (2023) further explored the impact of transformational leadership on innovative work behavior in the digital era and the effects of transformational leadership on knowledge sharing and its influence on innovative work

behavior in public organizations. Transformational leadership has a significant positive impact on innovative behavior and knowledge sharing. Knowledge sharing is crucial to an organization's success, impacting creativity, learning, and performance. Additionally, it emphasizes the influence of knowledge sharing on team atmosphere and employee life satisfaction, beyond the work itself (Ahmad and Karim 2019). García-Pérez et al. (2018) highlighted the criticality of knowledge sharing in organizational competitiveness. Their research focused on knowledge sharing within and between organizations, demonstrating through two case studies the importance of knowledge sharing for business development. Regardless of the nature of the business, individuals, groups, and decision-makers within the organization need to share critical knowledge to drive business development. These case studies emphasize the value of collaborative and human-centered knowledge sharing. Fauziyah and Rahayunus (2021) focused on the relationship between individual innovation capability and knowledge sharing, highlighting the importance of knowledge sharing in creating competitive advantages, especially supported by individual innovation capabilities. They found that individual innovation capability has a positive and significant impact on knowledge sharing and employee performance, further proving the key role of individual innovation capability in the relationship between knowledge sharing and employee performance. Nashir and Pratminingsih (2023) found that absorptive capacity positively affects knowledge sharing and job performance, with knowledge sharing acting as a mediator between absorptive capacity and job performance. Key factors for the successful promotion of knowledge management include strategy, culture, information technology, personnel, and organizational structure (Babu 2012). Information technology, knowledge management leadership, knowledge management culture, and knowledge management measurement are also important factors (Wong 2005). Additionally, organizational strategy definition, performance measurement standards, senior management involvement, and organizational culture significantly impact the successful implementation of knowledge management (Onofre and Teixeira 2022). These studies indicate that the successful implementation of knowledge management involves multiple factors, including strategy, culture, technology, personnel, and organizational structure, which collectively contribute to providing a competitive advantage for organizations.

## 2.2. Organizational Learning

Watad (2018) emphasized that, in IT-driven organizational changes, there is often a neglect of knowledge management and learning. They pointed out that organizations, when restructuring processes and improving productivity, tend to focus on immediate benefits while overlooking long-term knowledge management and learning strategies. This indicates that the managers' attention is usually limited and may not be able to handle both aspects simultaneously. This viewpoint reminds managers to pay more attention to the importance of knowledge management and learning in organizational change to ensure long-term development. Chuah and Law (2019) theoretically overviewed various concepts of organizational learning, describing it as the process of developing, retaining, and transferring knowledge within an organization. Although there is no unified definition of organizational learning, it is influential across many disciplines and closely related to knowledge management. Antunes and Pinheiro (2020) focused on knowledge management and learning in human resource management, emphasizing that an organization's knowledge management capabilities largely depend on its human resources, as they are the main force in creating, sharing, and applying knowledge. This underscores the importance of valuing knowledge management and learning in human resource management and viewing it as a key factor in organizational development. Hafner (2016) pointed out that the ability to effectively change and use knowledge is crucial for modern organizations. In today's era of knowledge explosion, organizations need to constantly adapt to changes and utilize knowledge to maintain competitive advantages. He emphasized the importance of incorporating organizational learning strategies into organizational development to ensure that organizations can timely absorb new knowledge and apply it in practice.

[Chou and Ramser \(2019\)](#) proposed a multi-level theoretical model, emphasizing that organizational learning is influenced by multiple levels and sources. They suggested that employees' spontaneous behaviors (such as upward help and voice) affect organizational learning and that developing leadership capital can promote organizational learning, offering strategies to encourage employee engagement in learning behaviors. [Kim and Lu \(2019\)](#) discussed the literature on learning organizations and organizational performance, highlighting the importance of learning organizations in improving organizational performance. They stated that the ability of learning organizations to connect with the external environment and the presence of leadership that supports learning enable these organizations to better cope with changes and challenges, maintaining a leading position in competitive environments.

[Seman and Mohamad \(2019\)](#) emphasized the role of organizational learning in promoting corporate innovation. Organizational learning helps organizations to continuously develop new ideas and solutions, thereby enhancing innovation capabilities. The study further pointed out that introducing transformational leadership styles helps to motivate employees to actively participate in the learning process, thereby driving innovation. [Argote et al. \(2020\)](#) divided organizational learning into four processes: searching, knowledge creation, knowledge retention, and knowledge transfer. This perspective provided a more detailed exploration of the processes and influencing factors of organizational learning. Through these four processes, organizations can continuously acquire new knowledge, create value, retain important information, and share knowledge within the organization. [Olejarski et al. \(2019\)](#) explored the importance of organizational learning from the perspective of public sector organizations, highlighting that organizational learning requires public institutions to change their norms and policies to better meet the changing demands and challenges. [You et al. \(2021\)](#) proposed organizational learning as a strategic approach to organizational change, emphasizing the importance of learning organizations in coping with change challenges and achieving organizational goals.

[Namada \(2018\)](#) regarded organizational learning as a key source of competitive advantage for contemporary business organizations, exploring different elements of organizational learning, including knowledge acquisition, knowledge distribution, information interpretation, and organizational memory, and how these elements influence organizational competitive advantage. [Pham and Hoang \(2019\)](#) confirmed the positive impact of organizational learning capabilities on business performance. They particularly found a positive correlation between management's commitment to learning, knowledge transfer, and business performance, encouraging companies to enhance business performance by strengthening organizational learning capabilities.

[Elkjaer \(2021\)](#) explored the theoretical construction of organizational learning, discussing the debates on the responsibility of organizational learning between practitioners and researchers, and suggested adopting a pragmatic learning theory to resolve these disputes. This study provided valuable insights into the future development of the field of organizational learning. Key success factors for organizational learning include strategy, culture, and technological factors ([Mas-Machuca and Martínez Costa 2012](#)). Organizational-level strategies and policies, IT readiness, performance and impact evaluation, personnel skills and expertise, and data quality are also critical to success ([Clark et al. 2020](#)). Moreover, organizational learning, as a strategic tool, not only enhances employees' knowledge and skills but also promotes organizational development and growth, creating a dynamic learning organization that plays an important role in achieving knowledge management and organizational goals ([Saadat and Saadat 2016](#)). Support from senior executives is equally crucial, as their participation and commitment can ensure the smooth progress and successful implementation of organizational learning and knowledge management programs ([Onofre and Teixeira 2022](#)).



### 2.3. Industry 4.0

#### 2.3.1. Operational Management

[Majstorovic et al. \(2020\)](#) believe that Industry 4.0 is a new model of technological system automation, based on the technological integration of the smart manufacturing concept, including the application of information and communication technologies such as cloud computing, big data analytics, artificial intelligence, and distributed control. They point out that ERP systems are evolving and can connect to IoT, big data analytics, AI, and cloud computing. [Polívka and Dvořáková \(2021\)](#) emphasize the significant impact of Industry 4.0 on the IT environment of organizations, especially ERP systems. [Rathnayake et al. \(2022\)](#) stress that Industry 4.0 technologies will increasingly rely on the application of ERP systems. Integrating Industry 4.0 technologies, such as IoT and RFID, into ERP systems can enhance ERP capabilities, providing more accurate analysis and forecasting. [Skrzeszewska and Patalas-Maliszewska \(2019\)](#) mention that Manufacturing Execution Systems (MES) are tools for executing internal business processes, particularly notable in the automotive manufacturing industry. Based on examples from two automotive manufacturing companies, they analyze the effectiveness of MES usage by maintenance department employees across business, tactical, and strategic management levels. [Goven-der et al. \(2019\)](#) explore the integration challenges between ERP and MES systems in the steel industry, which needs to integrate manufacturing and business systems for real-time decision-making and increased visibility of production processes. Additionally, the combination of MES and PLM systems can accelerate the promotion of Industry 4.0 ([D'Antonio et al. 2017](#)). [Popescu and Scarlat \(2022\)](#) discuss the need to integrate new paradigms of industrial automation and control systems in Industry 4.0 management. They examine the synergy of two concepts: cyber-physical SCADA systems and human-centric production, emphasizing their complementarity. This study highlights the role of SCADA systems in Industry 4.0 transformation. [Malik et al. \(2021\)](#) mention the construction modules of Industry 4.0, including cyber-physical systems, AI, robotics, cloud computing, and IoT, noting that SCADA systems play a key role in Industry 4.0 by monitoring, collecting, and processing real-time data to control industrial manufacturing processes. [Chang et al. \(2021\)](#) emphasize the importance of the SCADA architecture for achieving smart interconnected manufacturing factories, proposing a cloud-based analytics module for predictive maintenance (PDM) in Industry 4.0, using machine learning algorithms to analyze preprocessed data and provide predictive recommendations for production quality management. [Saxby et al. \(2020\)](#) point out how lean management methods support continuous improvement in the field of Industry 4.0. Lean management supports factors in Industry 4.0, including continuous improvement, supply chain involvement, pull systems, and customer-centric approaches. This study identifies that lean management can be supported by Industry 4.0 technologies. [Abdulnour et al. \(2022\)](#) introduce the digital transformation process of SMEs in the context of personalized mass production, emphasizing the importance of Industry 4.0 for the sustainable development of manufacturing enterprises and proposing the concept of Lean 4.0 to better adapt SMEs to personalized mass production environments. [Bordeleau et al. \(2018\)](#) mention that traditional business intelligence (BI) must adapt to the large volume of data from Industry 4.0 technologies and use this data for decision-making, thus creating value for companies. They point out that, by analyzing data and integrating it into strategic and operational activities, Industry 4.0 value is created. [Choi et al. \(2022\)](#) emphasize the impact of rapid business process changes in the era of Industry 4.0 on enterprise participants. They suggest promoting Industry 4.0 within organizations and review the positive impact of BI on decision-making within organizations. [Arana-Landín et al. \(2023\)](#) analyze the impact of Industry 4.0 technologies on energy efficiency, stating that the application of multiple Industry 4.0 technologies can significantly enhance decision-making capabilities for achieving higher energy efficiency. On the other hand, [Medojević et al. \(2019\)](#) focus on the impact of the Industry 4.0 concept on manufacturing energy and environmental management systems and overall manufacturing energy efficiency. Their research shows a significant correlation between the Industry 4.0 concept and manufac-

turing energy and environmental management systems. Additionally, SCM can enhance the capability of supply chain management through the connection and use of Industry 4.0-related technologies, improving production efficiency and management capabilities (Garay-Rondero 2019; Han et al. 2021).

### 2.3.2. Smart Production Applications

Lee et al. (2015) emphasized that the deployment of CPS systems is crucial for the infrastructure of Industry 4.0, highlighting that CPS systems enable information flow between physical factories and cyberspace. (Berger et al. 2016) pointed out that the introduction of CPS in Industry 4.0 has a significant impact on production scheduling and economic benefits. Through advanced information analysis, connected machines can operate more efficiently and flexibly, particularly in monitoring and controlling physical infrastructure (Pérez et al. 2016). Buhl et al. (2019) discussed the benefits of integrating dual-arm collaborative robot systems in smart factories and Industry 4.0 environments, especially for complex industrial assembly tasks. They highlighted the flexibility and synchronized movement capabilities of collaborative robot systems and their role in enhancing human work efficiency. Bragança et al. (2019) briefly outlined how collaborative robots support human resource needs in Industry 4.0 manufacturing environments. Gallala et al. (2022) noted the rapid increase in collaborative robots in manufacturing under the backdrop of Industry 4.0 and smart factories. Gualtieri et al. (2020) emphasized industrial collaborative robots as one of the main enabling technologies of Industry 4.0. (Berlak et al. 2021) found that the use of construction robots increased productivity by 75.6–91.3%. Jagatheesaperumal et al. (2022) reviewed the integration of artificial intelligence and big data in Industry 4.0, discussing their impact on manufacturing, with a particular focus on smart factory applications and the deployment of AI and big data in modern industries, highlighting advantages such as improved production efficiency and quality, and the challenges faced. Bécue et al. (2021) explored the application of artificial intelligence in manufacturing, particularly its role within the Industry 4.0 framework, emphasizing how AI technologies can enhance production efficiency and product quality, while also addressing related security issues, including data privacy and protection. Banitaan et al. (2023) underscored the critical role of artificial intelligence in Industry 4.0, viewing AI as a key technology for enhancing enterprise competitiveness, and mentioned its applications in production monitoring, optimization, and control. Çınar et al. (2020) discussed the widespread application of intelligent systems and AI in Industry 4.0, particularly machine learning and predictive maintenance methods. Due to digital transformation, many industrial devices generate vast amounts of operational and process condition data, which are used for automated fault detection and diagnosis, improving equipment utilization and extending its lifespan. Zonta et al. (2020) viewed machine maintenance in Industry 4.0 from another perspective, stating that the ability to predict future asset maintenance needs is crucial for improving production efficiency and quality. Arora (2023) proposed an automated defect diagnosis method using advanced image processing technology to improve quality control in Industry 4.0, highlighting that traditional manual inspection methods are time-consuming, arbitrary, and prone to errors, thus proposing this groundbreaking automated solution. Penumuru et al. (2019) introduced a general approach for automatic material identification using machine vision and machine learning technologies to enhance the cognitive capabilities of machines in the Industry 4.0 era. They used various classification algorithms to prepare and process material surface datasets and tested their robustness under different conditions. The results showed that the proposed method can effectively identify different material groups and be implemented in existing manufacturing settings without significant modifications, improving product quality. Ottogalli et al. (2019) proposed a framework using VR and AR technologies to simulate industrial processes, emphasizing the importance of such simulations for testing and studying new processes before deployment, introducing new features such as interaction between human workers and automated systems and flexible modeling for various domains and purposes. Bhattacharya (2022) discussed the use cases

and prospects of AR and VR technologies in industrial production processes, emphasizing their role in improving work efficiency and accuracy. [Ulmer et al. \(2019\)](#) highlighted the important role of AR and VR in virtual prototyping, manufacturing, and maintenance in Industry 4.0, noting that fully integrating these technologies into existing process structures is crucial for ensuring future competitiveness. [Li et al. \(2015\)](#) emphasized the importance of wireless networks in the Industry 4.0 framework, especially in smart factories and smart manufacturing systems. They introduced the concept of industrial wireless networks, discussed their characteristics, relevant technologies, and new architectures based on quality of service and data quality, while also highlighting design challenges and unresolved issues. [Alrashidi et al. \(2020\)](#) proposed an advanced clustering method to overcome challenges in monitoring and control applications, emphasizing the importance of extending the lifespan and minimizing power consumption, and proposed some optimization methods for the efficient operation of wireless sensor networks. [Alabi \(2017\)](#) pointed out the popularity and widespread application of 3D-printing technology globally, particularly in healthcare, automotive, aerospace, and manufacturing fields. They mentioned that big data and 3D-printing technologies are identified as key technologies driving Industry 4.0 and fostering innovation across various industries. [Chen and Lin \(2017\)](#) discussed the technical and managerial challenges faced by 3D printing, including time-consuming object design, material type limitations, accuracy, and productivity issues. [Malik et al. \(2022\)](#) explored the sustainability of 3D-printing technology within the Industry 4.0 framework, highlighting its advantages in weight reduction, waste reduction, and energy savings. They emphasized the importance of 3D printing as part of the Industry 4.0 technological revolution in achieving smart manufacturing across various industries. [Berlak et al. \(2021\)](#) calculated that the introduction of 3D printing in the construction industry resulted in a productivity increase of 5.3–41.4%. [Elbasani et al. \(2020\)](#) reviewed and elaborated on the core technologies of Industry 4.0 from the perspective of RFID technology, highlighting its role in IoT, big data, and other fields, and delved into its potential in Industry 4.0. [Gładysz et al. \(2023\)](#) emphasized the importance of RFID in Industry 4.0, exploring how the Industry 4.0 concept influences the adoption of RFID technology. [Hakeem et al. \(2020\)](#) focused on the application of RFID technology for material handling functions in Industry 4.0, stating that, with the advent of Industry 4.0, RFID technology is crucial for improving and effectively executing these functions. [Zeba and Čičak \(2020\)](#) discussed the importance of RFID technology in Industry 4.0, especially in resource planning, and highlighted RFID as a key technology supporting IoT, essential for achieving smart factories and efficient resource management. [Long et al. \(2018\)](#) emphasized the opportunities provided by Industry 4.0 for achieving flexible and efficient production. [Zant et al. \(2021\)](#) proposed a new approach to improving manufacturing operation flexibility, transforming rigid production systems into agile ones. They tested this approach on an Industry 4.0 platform, demonstrating its effectiveness, especially in quickly adapting to demand. [Gania et al. \(2017\)](#) discussed flexible manufacturing systems and the development of solutions based on flexibility concepts within Industry 4.0.

### 2.3.3. Information and Data Applications

[Alcaraz et al. \(2020\)](#) indicated that Industry 4.0 combines information technology (IT) and operational technology (OT), creating new opportunities to improve and optimize operational processes, products, and services. This combination creates a new industrial ecosystem but also leads to challenges in information security, as more connection points can lead to security vulnerabilities. [Cheng and Zhang \(2020\)](#) analyzed information security in the implementation of Industry 4.0 strategies, proposing a series of specific measures, from industrial control system security to encryption technologies, aimed at ensuring information security in Industry 4.0. [Pereira et al. \(2017\)](#) noted that Industry 4.0 leads to new technological trends, such as IoT and big data, while highlighting potential security vulnerabilities in these new technological solutions. They emphasized the security challenges for Industry 4.0 and called for increased awareness of security practices. [Khan and Javaid](#)



(2021) recognized IoT as a crucial component of Industry 4.0, with widespread applications in monitoring production systems in manufacturing and services. IoT promotes higher performance in Industry 4.0 and opens up new possibilities for manufacturing innovation and renewal. The primary function of IoT is to collect and share information through connected devices and machines, aiding in the creation of smart factories and providing better solutions, making IoT a key driver of Industry 4.0. Bisio et al. (2018) viewed IoT as one of the key technologies in Industry 4.0, utilizing smart, ubiquitous connected devices to achieve faster and more efficient production and management processes. Subramanian et al. (2021) emphasized the importance of cloud technology for the continuous advancement of Industry 4.0, particularly for the adoption by micro-, small, and medium enterprises (MSMEs). Cloud technology helps to centralize business information and provides a collaborative platform. Velásquez et al. (2018) noted that Industry 4.0 promotes the use of information and communication technology (ICT) in manufacturing processes to meet the demanding needs of new consumers. They highlighted cloud computing and big data as key technologies that support interconnected service networks and provide more flexible production processes. Atobishi et al. (2018) discussed the application of cloud computing and big data in Industry 4.0, which can accelerate the efficiency of enterprise production processes. Pisching et al. (2015) described the concept and characteristics of cloud-based manufacturing services in Industry 4.0, proposing the integration of cloud computing and IoT into the Internet of Services. Santos et al. (2017) discussed the role of big data in Industry 4.0, particularly in collecting, integrating, storing, processing, and analyzing data, enhancing production and data application capabilities, and making it more suitable for use in multinational enterprises.

#### 2.4. Competitiveness

Corporate competitiveness indicators include various aspects. Calış Duman and Akdemir (2021) mentioned profitability, revenue, and market share, stating that companies related to Industry 4.0 can improve their performance through changes in technological production models and the introduction of applications. However, while providing business performance, the production performance related to product quality, production efficiency, and cost reduction is closely linked to business performance (Amoako-Gyampah and Acquah 2008). Additionally, Yu et al. (2016) also pointed out that related cost and quality improvements can further enhance a company's profitability and revenue growth.

### 3. Research Design

#### 3.1. Research Framework

This study focuses on the Taiwanese metal industry to investigate the impact of promoting knowledge management and organizational learning on Industry 4.0 and competitiveness. The conceptual framework of this study is shown in Figure 1.

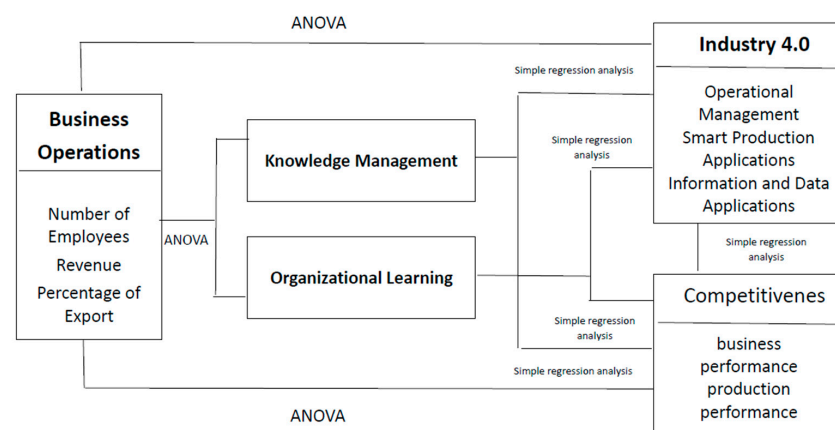


Figure 1. Research framework.

### 3.2. Research Subjects

This study targeted the Taiwanese metal industry SMEs as the research population. According to the Ministry of Economic Affairs of Taiwan, the upper limit for the number of employees in SMEs is 200. According to the statistics from the Department of Statistics, Ministry of Economic Affairs, Taiwan, there are 23,000 registered metal industry companies in Taiwan, of which 95% are SMEs.

### 3.3. Data Collection

The survey period for this study was from March 2024 to April 2024. To ensure that the respondents were representative and indicative of the industry, the survey questionnaires were distributed to members of relevant associations in the Taiwanese metal industry. For a comprehensive and reliable survey, the survey was sent via email to senior executives (managers of the management department, HR department, manufacturing department, or R&D department). Responses were collected through an online Google form, yielding a total of 129 valid samples with a response rate of 24%.

### 3.4. Survey Design

Based on the collected literature, indicators were designed to explore knowledge management, organizational learning promotion, Industry 4.0, and competitiveness. Three experts from relevant fields were invited to provide expert opinions, which helped to establish a valid questionnaire for this study. The questionnaire covers the company background as defined in Table 1.

**Table 1.** Company background definitions.

	Number of Employees	Revenue (100 Million)	Percentage of Export (%)
1	0~25	0~1	0~25
2	26~50	1~2	26~50
3	51~75	2~3	51~75
4	76 or more	3 or more	75 or more

The survey items for this study included promoting knowledge management and organizational learning, with Industry 4.0 divided into operational management, smart production applications, and information and data applications. Competitiveness was divided into “business performance and production performance.” A Likert five-point scale was used, with responses ranging from “strongly agree” (5), “agree” (4), “neutral” (3), “disagree” (2), to “strongly disagree” (1). Higher scores indicate a higher degree of actual conformity to the situation. A pilot survey was conducted, yielding 14 responses, and a Pearson correlation analysis was performed. The results show significant correlations between promoting knowledge management, organizational learning, Industry 4.0, and competitiveness, forming the basis for the full survey.

### 3.5. Data Processing and Statistical Methods

After collecting the survey data, all valid responses were coded and entered into a computer database. For statistical analysis, SPSS for Windows version 27 was used. The following statistical analyses were conducted:

#### 3.5.1. Dimensional ANOVA Analysis

Business operations were used as the independent variables, divided into employee numbers, company revenue, and export. Knowledge management, organizational learning promotion, Industry 4.0, and competitiveness were used as the dependent variables. A one-way ANOVA was conducted. If significant differences were found, Scheffé’s post hoc comparisons were performed to understand the differences.

### 3.5.2. Pearson Correlation Analysis

We used a correlation analysis on each dimension of knowledge management, organizational learning promotion, Industry 4.0, and competitiveness to understand the relationships between the variables.

### 3.5.3. Dimensional Simple Regression Analysis

We used simple regression models to examine the relationships between promoting knowledge management, Industry 4.0 (operational management, smart production applications, and information and data applications), and competitiveness (business performance and production performance).

We used simple regression models to examine the relationships between promoting organizational learning, Industry 4.0 (operational management, smart production applications, and information and data applications), and competitiveness (business performance and production performance).

We used simple regression models to examine the relationship between Industry 4.0 and competitiveness.

## 4. Method Analysis

### 4.1. ANOVA Method Analysis

In the ANOVA analysis of the employee numbers on the four variables (Table 2), the results show significant impacts on knowledge management promotion, organizational learning promotion, and Industry 4.0, but no significant impact on competitiveness. Knowledge management promotion has a significant impact ( $p < 0.01^{**}$ ), with the post hoc comparison results indicating that the third group scored higher than the first and fourth groups. Organizational learning promotion has a significant impact ( $p < 0.05^{*}$ ), with the post hoc comparison results showing that the third group scored higher than the second, fourth, and first groups. The introduction of Industry 4.0 has a significant impact ( $p < 0.01^{**}$ ), with the post hoc comparison results indicating that the third group scored higher than the fourth, second, and first groups. In terms of competitiveness, there is no significant impact ( $p = 0.284$ ); this can be explained by the fact that competitiveness is a part of overall corporate performance indicators, and it is unlikely to show significant differences solely based on the number of employees.

**Table 2.** Impact of employee numbers on knowledge management promotion, organizational learning promotion, Industry 4.0, and competitiveness.

Vector	Source of Variation	SS	df	MS	F	p	Post Hoc
Knowledge management	Number of workers	9.736	3	3.245	4.929	0.003 **	3 > 1 > 4 > 2
Organizational learning	Number of workers	5.600	3	1.867	3.860	0.011 *	3 > 2 > 4 > 2
Industry 4.0	Number of workers	8.552	3	2.851	5.928	0.001 **	3 > 4 > 2 > 1
Competitiveness	Number of workers	10.398	3	3.466	1.280	0.284	

$N = 129$ ; \*,  $p < 0.05$ ; \*\*,  $p < 0.01$ .

The ANOVA analysis of company revenue on the four variables (Table 3) shows that there are highly significant impacts on knowledge management, organizational learning promotion, and Industry 4.0, while the impact on competitiveness is relatively lower but still significant. Specifically, knowledge management promotion has a significant impact ( $p < 0.01$ ). The post hoc comparison results indicate that the third group scored higher than the fourth, first, and second groups. Organizational learning promotion has a very significant impact ( $p < 0.001$ ). The post hoc comparison results show that the third group scored higher than the fourth and first groups. The introduction of Industry 4.0 has a highly significant impact ( $p < 0.001$ ). The post hoc comparison results indicate that the fourth group scored higher than the third, first, and second groups. In terms of competitiveness,

there is a significant impact ( $p < 0.05$ ). The post hoc comparison results show that the fourth group scored significantly higher than the third, second, and first groups.

**Table 3.** Impact of company revenue on knowledge management promotion, organizational learning promotion, Industry 4.0, and competitiveness.

Vector	Source of Variation	SS	df	MS	F	p	Post Hoc
Knowledge management	revenue	11.286	3	3.762	5.823	0.001 **	3 > 4 > 1 > 2
Organizational learning	revenue	10.560	3	3.520	7.929	0.000 ***	3 > 4 > 1 > 2
Industry 4.0	revenue	11.270	3	3.757	8.183	0.000 ***	4 > 3 > 1 > 2
Competitiveness	revenue	28.454	3	9.485	3.699	0.014 *	4 > 3 > 2 > 1

$N = 129$ ; \*,  $p < 0.05$ ; \*\*,  $p < 0.01$ ; \*\*\*,  $p < 0.001$ .

In the ANOVA analysis of the export ratio on the four variables (Table 4), the results show no significant impact on knowledge management promotion, organizational learning promotion, and Industry 4.0. Specifically, the  $p$ -value for knowledge management promotion is 0.496, for organizational learning promotion is 0.154, and for the introduction of Industry 4.0 is 0.120, indicating that the export ratio does not have a significant impact on these three variables. However, for competitiveness, the  $p$ -value is 0.004, indicating a significant impact. The post hoc comparison results show that the fourth group scored significantly higher than the third, second, and first groups; this can be explained by the fact that companies with higher export levels generally have higher-value products, which in turn can enhance their competitive advantage.

**Table 4.** Impact of export on knowledge management promotion, organizational learning promotion, Industry 4.0, and competitiveness.

Vector	Source of Variation	SS	df	MS	F	p	Post Hoc
Knowledge management	Export	1.733	3	0.578	0.799	0.496	
Organizational learning	Export	2.708	3	0.903	1.782	0.154	
Industry 4.0	Export	3.121	3	1.040	1.984	0.120	
Competitiveness	Export	35.758	3	11.919	4.757	0.004 **	4 > 3 > 2 > 1

$N = 129$ ; \*\*,  $p < 0.01$ .

#### 4.2. Pearson Correlation Analysis

The results of the product-moment correlation analysis between knowledge management promotion, organizational learning promotion, operational management, smart production applications, information and data applications, business performance, and production performance are shown in Table 5. The following is a brief description of the correlations between variables and their significance levels:

**Table 5.** Correlation analysis for knowledge management, organizational learning, operational management, smart production applications, information and data applications, business performance, and production performance.

Related Factor	1	2	3	4	5	6	7
1. Knowledge Management	1						
2. Organizational Learning	0.562 ***	1					
3. Operational Management	0.430 ***	0.631 ***	1				
4. Smart Production Applications	0.207 *	0.512 ***	0.684 ***	1			
5. Information and Data Applications	0.168	0.389 ***	0.476 ***	0.687 ***	1		
6. Business performance	0.346 ***	0.518 ***	0.480 ***	0.491 ***	0.526 ***	1	
7. Production performance	0.211 *	0.437 ***	0.390 ***	0.449 ***	0.456 ***	0.684 ***	1

$N = 129$ ; \*,  $p < 0.05$ ; \*\*\*,  $p < 0.001$ .

Knowledge management and organizational learning show a strong positive correlation ( $r = 0.562, p < 0.001$ ). Knowledge management has significant correlations with operational management ( $r = 0.430, p < 0.001$ ), smart production applications ( $r = 0.207, p < 0.05$ ), business performance ( $r = 0.346, p < 0.001$ ), and production performance ( $r = 0.211, p < 0.05$ ). There is no significant correlation with information and data applications ( $r = 0.168$ ).

Organizational learning has highly significant correlations with operational management ( $r = 0.631, p < 0.001$ ), smart production applications ( $r = 0.512, p < 0.001$ ), information technology ( $r = 0.389, p < 0.001$ ), business performance ( $r = 0.518, p < 0.001$ ), and production performance ( $r = 0.437, p < 0.001$ ).

Operational management and smart production applications show a strong positive correlation ( $r = 0.684, p < 0.001$ ). There are significant correlations with information and data applications ( $r = 0.476, p < 0.001$ ), business performance ( $r = 0.480, p < 0.001$ ), and production performance ( $r = 0.390, p < 0.001$ ).

Smart production applications and information and data applications show a strong positive correlation ( $r = 0.687, p < 0.001$ ). There are significant correlations with business performance ( $r = 0.491, p < 0.001$ ) and production performance ( $r = 0.449, p < 0.001$ ).

Information and data applications and business performance show a strong positive correlation ( $r = 0.526, p < 0.001$ ), and a significant correlation with production performance ( $r = 0.456, p < 0.001$ ).

The correlation between business performance and production performance is strong and positive ( $r = 0.684, p < 0.001$ ).

#### 4.3. Simple Regression Analysis Method

Examining the impact of knowledge management on operational management in Table 6, the results show that the unstandardized coefficient (B) of knowledge management is 0.433, the standardized coefficient ( $\beta$ ) is 0.430, the t-value is 5.373, and the p-value is lower than 0.001, indicating statistical significance. The related coefficient  $\Delta R^2$  is 0.185, indicating that knowledge management has a moderate positive impact on operational management, explaining 18.5% of the variance.

**Table 6.** Simple regression analysis of the impact of knowledge management on operational management.

B	SEB	$\beta$	t	p
0.433	0.081	0.430 ***	5.373	<0.001

Note:  $\Delta R^2 = 0.185$ .

Examining the impact of knowledge management on smart manufacturing applications in Table 7, the results show that the unstandardized coefficient (B) of knowledge management is 0.187, the standardized coefficient ( $\beta$ ) is 0.207, the t-value is 2.380, and the p-value is 0.019, indicating statistical significance. The related coefficient  $\Delta R^2$  is 0.043, indicating that knowledge management has a significant but relatively low positive impact on smart manufacturing applications, explaining 4.3% of the variance.

**Table 7.** Simple regression analysis of the impact of knowledge management on smart manufacturing applications.

B	SEB	$\beta$	t	p
0.187	0.079	0.207 *	2.380	0.019

Note:  $\Delta R^2 = 0.043$ .

Examining the impact of knowledge management on information and data application in Table 8, the results show that the unstandardized coefficient (B) of knowledge management is 0.195, the standardized coefficient ( $\beta$ ) is 0.168, the t-value is 1.923, and the p-value is 0.057. The results are close to but do not reach the level of statistical significance.



The related coefficient  $\Delta R^2$  is 0.028, indicating that knowledge management has a slight positive impact on information and data application, explaining 2.8% of the variance.

**Table 8.** Simple regression analysis of the impact of knowledge management on information and data application.

B	SEB	$\beta$	t	p
0.195	0.101	0.168	1.923	0.057

Note:  $\Delta R^2 = 0.028$ .

Examining the impact of knowledge management on business performance in Table 9, the results show that the unstandardized coefficient (B) of knowledge management is 0.378, the standardized coefficient ( $\beta$ ) is 0.346, the t-value is 4.154, and the p-value is lower than 0.001, indicating a high level of statistical significance. The related coefficient  $\Delta R^2$  is 0.120, indicating that knowledge management has a significant positive impact on business performance, explaining 12% of the variance.

**Table 9.** Simple regression analysis of the impact of knowledge management on business performance.

B	SEB	$\beta$	t	p
0.378	0.091	0.346 ***	4.154	<0.001

Note:  $\Delta R^2 = 0.012$ .

Examining the impact of knowledge management on production performance in Table 10, the results show that the unstandardized coefficient (B) of knowledge management is 0.258, the standardized coefficient ( $\beta$ ) is 0.211, the t-value is 2.433, and the p-value is 0.016, indicating statistical significance. The related coefficient  $\Delta R^2$  is 0.045, indicating that knowledge management has a significant positive impact on production performance, explaining 4.5% of the variance.

**Table 10.** Simple regression analysis of the impact of knowledge management on production performance.

B	SEB	$\beta$	t	p
0.258	0.106	0.211 *	2.433	0.016

Note:  $\Delta R^2 = 0.045$ .

Examining the impact of organizational learning on operational management in Table 11, the results show that the unstandardized coefficient (B) of organizational learning is 0.750, the standardized coefficient ( $\beta$ ) is 0.631, the t-value is 9.165, and the p-value is lower than 0.001, indicating a high level of statistical significance. The related coefficient  $\Delta R^2$  is 0.398, indicating that organizational learning has a significant positive impact on operational management, explaining 39.8% of the variance.

**Table 11.** Simple regression analysis of the impact of organizational learning on operational management.

B	SEB	$\beta$	t	p
0.750	0.082	0.631 ***	9.165	<0.001

Note:  $\Delta R^2 = 0.398$ .

Examining the impact of organizational learning on smart manufacturing in Table 12, the results show that the unstandardized coefficient (B) of organizational learning is 0.547, the standardized coefficient ( $\beta$ ) is 0.512, the t-value is 6.721, and the p-value is lower than 0.001, indicating a high level of statistical significance. The related coefficient  $\Delta R^2$  is 0.262, indicating that organizational learning has a significant positive impact on smart manufacturing, explaining 26.2% of the variance.

**Table 12.** Simple regression analysis of the impact of organizational learning on smart manufacturing.

<b>B</b>	<b>SEB</b>	<b><math>\beta</math></b>	<b>t</b>	<b>p</b>
0.547	0.081	0.512 ***	6.721	<0.001

Note:  $\Delta R^2 = 0.262$ .

Examining the impact of organizational learning on information and data applications in Table 13, the results show that the unstandardized coefficient (B) of organizational learning is 0.533, the standardized coefficient ( $\beta$ ) is 0.389, the t-value is 4.762, and the p-value is lower than 0.001, indicating a high level of statistical significance. The related coefficient  $\Delta R^2$  is 0.152, indicating that organizational learning has a significant positive impact on information and data applications, explaining 15.2% of the variance.

**Table 13.** Simple regression analysis of the impact of organizational learning on information and data applications.

<b>B</b>	<b>SEB</b>	<b><math>\beta</math></b>	<b>t</b>	<b>p</b>
0.533	0.112	0.389 ***	4.762	<0.001

Note:  $\Delta R^2 = 0.152$ .

Examining the impact of organizational learning on business performance in Table 14, the results show that the unstandardized coefficient (B) of organizational learning is 0.669, the standardized coefficient ( $\beta$ ) is 0.518, the t-value is 6.831, and the p-value is lower than 0.001, indicating a high level of statistical significance. The related coefficient  $\Delta R^2$  is 0.269, indicating that organizational learning has a significant positive impact on business performance, explaining 26.9% of the variance.

**Table 14.** Simple regression analysis of the impact of organizational learning on business performance.

<b>B</b>	<b>SEB</b>	<b><math>\beta</math></b>	<b>t</b>	<b>p</b>
0.669	0.098	0.518 ***	6.831	<0.001

Note:  $\Delta R^2 = 0.269$ .

Examining the impact of organizational learning on production performance in Table 15, the results show that the unstandardized coefficient (B) of organizational learning is 0.629, the standardized coefficient ( $\beta$ ) is 0.437, the t-value is 5.471, and the p-value is lower than 0.001, indicating a high level of statistical significance. The related coefficient (R) is 0.437, and  $\Delta R^2$  is 0.191, indicating that organizational learning has a significant positive impact on production performance, explaining 19.1% of the variance.

**Table 15.** Simple regression analysis of the impact of organizational learning on production performance.

<b>B</b>	<b>SEB</b>	<b><math>\beta</math></b>	<b>t</b>	<b>p</b>
0.629	0.115	0.437 ***	5.471	<0.001

Note:  $\Delta R^2 = 0.191$ .

Examining the impact of Industry 4.0 on competitiveness in Table 16, the results show that the unstandardized coefficient (B) of Industry 4.0 is 1.203, the standardized coefficient ( $\beta$ ) is 0.534, the t-value is 7.113, and the p-value is lower than 0.001, indicating a high level of statistical significance. The related coefficient  $\Delta R^2$  is 0.285, indicating that Industry 4.0 has a significant positive impact on competitiveness, explaining 28.5% of the variance.

**Table 16.** Simple regression analysis of the impact of Industry 4.0 on competitiveness.

<b>B</b>	<b>SEB</b>	<b><math>\beta</math></b>	<b>t</b>	<b>p</b>
1.203	0.169	0.534 ***	7.113	<0.001

Note:  $\Delta R^2 = 0.285$ .

## 5. Research Conclusions

### 5.1. Conclusions

The metal industry in Taiwan is composed of 95% small- and medium-sized enterprises (SMEs). The metal industry chain is extensive, covering upstream, midstream, and downstream sectors, including steel, hand tools, casting, fasteners, plumbing hardware, surface treatment, and heat treatment. These enterprises are generally small in scale and operate with a specialized division of labor. Therefore, for enterprises to promote transformation, upgrade, and enhance competitiveness through the introduction of new technologies, it is necessary to simultaneously promote knowledge management and organizational learning. The findings of this study can be summarized as follows:

1. Through this study, it was observed that companies with relatively high organizational learning promotion and Industry 4.0 significance tend to have higher revenues. This can be explained by the fact that a higher degree of organizational learning promotion helps companies to apply more new technologies or enhance R&D capabilities, thus driving revenue growth. Similarly, companies with a higher degree of Industry 4.0 adoption can leverage production technology advantages to increase revenues. This result aligns with global government policies and resources supporting enterprises in adopting Industry 4.0 technologies to aid in transformation and sustainable operations. Furthermore, it was observed that knowledge management promotion, organizational learning promotion, and Industry 4.0 adoption do not significantly impact export proportions, except for competitiveness. Companies with higher export proportions tend to have market advantages in their products, thereby enhancing business performance and production efficiency. Regarding the number of employees, significant impacts were found on knowledge management promotion, organizational learning promotion, and Industry 4.0 adoption, especially in groups with 51–75 employees. This suggests that reaching a certain scale in the number of employees can facilitate the establishment of knowledge management and organizational learning mechanisms. For Industry 4.0 adoption, companies with 51–75 and over 76 employees have higher adoption levels, indicating that the scale of the workforce affects the extent of Industry 4.0 adoption.
2. The transformation and upgrading of SMEs can enhance competitiveness, with Industry 4.0 adoption being a global industrial development trend. Regarding the correlation between knowledge management and the three aspects of Industry 4.0, operational management had the highest correlation, followed by intelligent production applications, while information and data applications showed no significant correlation. This study's findings are consistent with those of [Bettioli et al. \(2022\)](#), showing that knowledge management can influence operational management and intelligent production applications. However, unlike their findings, this study did not find a significant impact on information and data applications, possibly because this study focused on SMEs that have already adopted operational management and intelligent production technologies, leading to more knowledge sharing and exchange within the organization.
3. Promoting organizational learning can enhance the technological capabilities and competitiveness of SMEs. This study observed that organizational learning can facilitate the adoption of relevant technologies in the three aspects of Industry 4.0: operational management, intelligent production applications, and information and data applications. The findings are consistent with those of [Srivastava et al. \(2022\)](#) and [Prashar et al. \(2024\)](#), indicating that a comprehensive learning mechanism within

the organization, supported by senior management, is crucial for transformation and upgrading. Organizational learning can serve as a key strategy for promoting enterprise transformation and accelerating the upgrading process.

4. The adoption of Industry 4.0 technologies is an optimal tool for SME transformation, enhancing business performance and production efficiency. The findings of this study are consistent with those of [Lavinsaa et al. \(2020\)](#), [Calış Duman and Akdemir \(2021\)](#), and [Chauhan et al. \(2021\)](#), which show that promoting Industry 4.0 can enhance competitiveness. Competitiveness is key to the sustainable operation of enterprises, leading governments to invest resources in supporting SMEs to adopt Industry 4.0, thereby driving sustainable national industrial development.

In summary, knowledge management and organizational learning can drive enterprises to adopt Industry 4.0. This study finds that SMEs need to establish a short-, medium-, and long-term transformation roadmap with set goals and benefits for each stage to verify if the transformation meets the expected goals. For SMEs to adopt new technologies such as Industry 4.0, they need to fully utilize these technologies as a strategy to enhance competitiveness. Promoting knowledge management is crucial, as the dissemination and application of new knowledge within the organization is key to SME transformation. Internalizing new knowledge among employees facilitates the expected benefits of new technology adoption. Promoting organizational learning is also critical for new technology adoption within the organization, thereby enhancing competitiveness. Hence, promoting knowledge management and organizational learning effectively drives Industry 4.0 adoption, enhancing competitiveness, aligning with the research objectives, and serving as a strategy for future technology adoption to ensure successful transformation and sustainable operation.

## 5.2. Research Limitations

The limitations of this study include the fact that Industry 4.0 has become a global industrial development trend, yet this study is limited to a single country, Taiwan, and a single industry. The Taiwanese government prioritizes Industry 4.0 as a key policy for industrial transformation, providing enterprises with substantial resources and reducing obstacles to Industry 4.0 adoption.

## 5.3. Future Research Recommendations

As Industry 4.0 has become an industrial development trend, future research and surveys should expand the industry scope and conduct comparative analyses across different industries. Further investigation is needed to explore whether the transformation promotion results differ across industries and countries with varying background factors.

Additionally, knowledge management, organizational learning, and Industry 4.0 involve changes in business strategies and technology applications. Future research should explore the key success factors and obstacles in promoting these three aspects simultaneously.

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