Key action strategies for introducing smart manufacturing to small manufacturing industries

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Abstract

The global business environment is undergoing significant changes due to the impact of COVID-19 and shifts in workforce demographics, making organizational change an inevitable trend. In this context, the smooth adoption of smart manufacturing in the manufacturing industry is crucial for enhancing organizational value. Through a literature review, this study consolidated key factors related to organizational innovation and the implementation of smart manufacturing. The analytic hierarchy process (AHP) was employed to identify the prioritized sequence of key strategic actions for innovative operations. The results indicated that among 27 assessment indicators, motivation is the most crucial factor for organizational innovation/change. Subsequently, organizations must also prioritize strategic human resource deployment to accelerate the development of long-term organizational goals. This study further examined solutions to ensure both talent and organizational growth during the transformation of innovation strategies.

Introduction

Amid a shrinking workforce and growing international competition, Taiwan is facing significant changes in the labor supply–demand structure, which is causing long-term labor shortages in various industries (Wang et al., 2017). Additionally, the sudden onset of the COVID-19 pandemic has altered people's lifestyles, creating significant social and economic challenges for organizations. In a severely fluctuating environment, organizations are compelled to undergo rapid transformation (Brammer et al., 2020).

In recent years, the U.S.–China trade war and the COVID-19 pandemic have caused international raw material prices to surge, escalating operational costs for businesses and further decreasing organizational profits (Bown, 2021; Mostafiz et al., 2022). To cope with these changes, small manufacturing businesses must optimize their production management mechanisms to reduce production costs and meet current market demands (Horváth & Szabó, 2019). Smart manufacturing can enhance production efficiency while reducing labor costs (Abd Hamid et al., 2022). Therefore, compared to traditional manufacturing, smart manufacturing systems are considered a production method with various advantages (Kamble et al., 2020).

The introduction of smart manufacturing aims to achieve optimized operational efficiency and plays a crucial role in the current industrial era (Phuyal et al., 2020). However, internal conflicts often arise between decision-makers and implementers within the organization concerning smart manufacturing (Clerkin & Jones, 2013). Such conflicts are significant contributors to the lack of success in organizational change processes (Behestifar & Zare, 2013), and they stem from individuals seeking to maximize their own utility and attempting to influence decision-making behaviors (Teng & Cummings, 2002). Ignoring the balance and interaction between resources and capabilities may lead to internal conflicts, hindering successful organizational change (Teng & Cummings, 2002).

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Organizational change not only involves changes in the organization’s functions and structure but also impacts the capabilities of the workforce (Bonanomi et al., 2020; Tschang & Almirall, 2021). The shared growth of core teams and the enhancement of human capital are crucial issues of concern for business owners in the process of organizational change (Del Giudice et al., 2021). Researchers of resource-based theory have typically regarded knowledge and capability to be the unique resources of an organization, with the primary avenue for acquiring these being through learning (Alvarez & Busenitz, 2001). Organizational knowledge and capabilities are not simply the sum of individual employees’ knowledge and abilities, but rather the organic combination thereof (Bhatt, 2000). Therefore, organizational learning not only enhances individual knowledge and abilities but also facilitates the transformation of individual knowledge and abilities into organizational knowledge and capabilities, thereby generating greater momentum for organizational change (Wiklund & Shepherd, 2003).

Internal conflicts within the organization and differences in cross-departmental action strategies may lead to failure in organizational change. A similar trajectory can also be observed when introducing smart manufacturing to corporate operations. While smart manufacturing has emerged as a transformative initiative in recent years globally, there exists divergence in the strategies employed for its implementation. Furthermore, the nature of this industry is a critical factor influencing the success of smart manufacturing adoption (Pfeifer, 2021), and perspectives on its implementation may vary based on different business functions. To address this issue, we examined the introduction of smart manufacturing to small enterprises to identify the knowing-in-action differences between human resource managers and smart manufacturing experts and formulate a strategy to reduce internal conflict and increase the success rate of organizational change. The research process began with a review of relevant literature, consolidating the indicators related to innovation strategies and organizational change, as well as talent-related issues that may arise in the era of smart manufacturing. Subsequently, an Analytic Hierarchy Process (AHP) analysis was conducted (Ishizaka & Labib, 2011), involving surveys of human resource managers and smart manufacturing experts. Finally, based on the results obtained from the AHP survey, key action strategies for small- and medium-sized manufacturing enterprises facing organizational change in smart manufacturing are summarized.

This article is organized as follows: following the introduction section, the second section comprises a literature review encompassing theoretical foundations and the progress of prior research. This serves to elucidate the relationship between theory and the current study, while also highlighting deficiencies in previous research to underscore the significance and value of the present study. The third section introduces the process of research data collection and the methods employed for data analysis. Subsequently, in the fourth section, the results of the data analysis are explicated. The fifth section delves into a comprehensive discussion of the research findings, elucidating not only their theoretical implications but also proposing practical contributions. Finally, the article concludes by summarizing key points, presenting suggestions, discussing future research directions, and outlining the limitations of the study.

**Literature Review**

**The current situation of the smart manufacturing industry**

Industry 4.0, coined in Germany, is widely considered to be a roadmap for the fourth industrial revolution (Fuchs, 2018). Since then, various countries have launched similar plans (Yang & Gu, 2021), resulting in a substantial movement comparable to the first industrial revolution (Rüßmann et al., 2015). This movement has had a profound interactive effect on manufacturing behaviors (Rossini et al., 2019). The concept of Industry 4.0 was first introduced at Hannover Messe in 2011. Two years later, Henning (2013) presented the final report *Recommendations for implementing the strategic initiative INDUSTRIE 4.0* at the same fair. The report identified the working groups involved in Industry 4.0, including the German government, companies (such as ABB, BMW, and Siemens), research institutions, and universities, predicting that Industry 4.0 is expected to address current global challenges (Sorooshian & Panigrahi, 2020).

The key technologies of Industry 4.0 lie primarily in information and communication, including machine-to-machine (M2M) coordination, big data processing, and system collaboration. Such systems include, but are not limited to, development, sales, supply chain management, enterprise resource planning (ERP), and product lifecycle management (PLM). Subsequently, smart manufacturing is seen as an integrated and applied process of technological advancements developed by humanity (Henning, 2013; Mrugalska & Wyrwicka, 2017). In other words, its main function and benefit are to elevate lean production to the level of precision production and operations (Ghahramani et al., 2020). The key to precision production and operations lies in the rawest big data, generated by systems or devices without manual input. The data are then used in machine learning to create models capable of producing accurate predictions and feedback on information flow, logistics, cash flow, and human flow instantaneously (Oztelme & Gursev, 2020). Given the characteristics of smart manufacturing, Oztelme and Gursev (2020) further emphasized the need to distinguish four aspects when implementing smart manufacturing, including (1) differentiating between Industry 4.0 and automation, (2) understanding the technical progression of the equipment and systems involved in each stage from Industry 1.0 to Industry 4.0, (3) clearly defining goals for each step, and (4) understanding the level of intelligence of each module internally.

In summary, Industry 4.0 has gained global attention. The realization of smart manufacturing will push lean production to precision production and operations. Achieving smart manufacturing lies in training models with the rawest big data. When implementing smart manufacturing, it is crucial to distinguish clearly between Industry 4.0 and automation, understand the technical progression of the equipment and systems, define clear goals for each step, and understand the intelligence level of each module.
Innovation strategy

Innovation strategy is regarded as a crucial driver for companies to achieve competitive advantage and long-term success (Badanin, 2023; Lutchenko et al., 2021). This impact is not only reflected in product or service innovation but also extends to innovations in organizational structure, marketing methods, and technological applications, among other aspects (Thranie et al., 2010). The goal of innovation strategy is to enhance the competitiveness of enterprises, meet market demands, and adapt to changing environments (Bowonder et al., 2010; Zhou & Li, 2010).

According to Schumpeter (1942), innovation is considered the primary driving force behind economic growth. He introduced the concept of creative destruction theory, advocating the creation of superior results by disrupting existing economic models and driving the renewal of industry technology through the effect of creative destruction (Tüllüce & Yurtkur, 2015). Porter (1985) emphasized the importance of innovation in achieving competitive advantage, particularly the positive effects of innovation on industry structure, and maintained that cost leadership is a strategy that achieves cost leadership goals through process improvement and innovation. Wijekoon et al. (2021) argued that although there are differences in the classification and approaches of innovation strategies, the content and scope are actually quite similar, primarily comprising leading products and technologies, market entry timing, research and development expenditures and investments, proportion of revenue associated with new products, and the type, degree, and source of innovation. The aforementioned studies highlighted the critical role of innovation strategy in the success and competitive advantage of enterprises and emphasized the importance of innovation at different levels and aspects for businesses. In the realm of current industrial innovation, the implementation of smart manufacturing is poised to bring benefits such as organizational performance improvement and sustainable enhancement of competitive advantages for manufacturers, suppliers, and customers (Kamble et al., 2020; Narwane et al., 2022). Therefore, it can be regarded as a strategy for innovation.

The issue of smart manufacturing talent

The field of smart manufacturing is facing a severe talent shortage. Therefore, new talent development models are urgently needed (Zhang et al., 2023). Smart manufacturing is an interdisciplinary industry. Only by resolving the gap between talent development and industry demand can the shortage of talent in the industry be resolved (Qin et al., 2023). According to a survey and forecast report by the Taiwan National Development Council, one of the main reasons for the shortage of smart manufacturing talent is the “insufficient supply of graduates”, accounting for 26.3% of the overall reasons, followed by the “inadequate skills or qualifications of existing employees,” accounting for 26.0%. The report also highlighted that "inadequate skills or qualifications of existing employees" is the primary cause of talent shortages in industries, such as communication, smart machinery, offshore wind power generation, semiconductor manufacturing, materials science, tourism, and entertainment (National Development Council, 2021). Furthermore, Pfeifer (2021) highlights that differences in industrial characteristics are also one of the reasons influencing the talent gap in smart manufacturing. Therefore, as smart manufacturing advances, the manufacturing industry must address the challenges posed by changes in the overall environmental structure, including formulating measures to prevent talent shortages or facilitate job succession (reserve managers; Vereycken et al., 2021).

Given the diverse industrial landscape shaped by technological innovation, competitive requirements, environmental changes, and societal trends, developing organizational strategies based on organizational vision and goals that benefit innovation and sustainable management has become a global challenge (Ishizaka & Labib, 2011; Kerin & Pham, 2020). The workplace undergoes continuous changes as organizations expand their scale of operations, enhance efficiency, and explore new opportunities through the use of technology to achieve business strategies. Therefore, organizations must focus on progressively innovative organizational structures through strategic human resource deployment and implement action strategies during the innovation process to reduce resistance and rejection (Meindl et al., 2021; Szász et al., 2021; Wang et al., 2021). Yet, targeted action strategies to address issues arising from organizational changes and the introduction of smart manufacturing have yet to be thoroughly explored. The main purpose of this study was to close this knowledge gap.

Research and Methodology

The AHP is a structured technique developed by Saaty at the University of Pittsburgh in the 1970s. It is a process for organizing and analyzing complex decision-making based on mathematics and psychology (Moreno-Jiménez & Vargas, 2018; Saaty & Vargas, 2012). The AHP utilizes the individual experiences of experts and pairwise comparisons to estimate the relative sizes of factors (Liu et al., 2020). In the evaluation of multi-attribute decision-making, the weight values of each attribute can significantly impact the selection of solutions (Saaty, 2008). The process of introducing smart manufacturing is complex and involves extensive considerations. Therefore, a method that can systematically address and consider the problem from multiple perspectives is needed to cover all of the characteristics of the issues thoroughly. In this context, we adopted the AHP as the method for calculating weighted values and priority orders during the research process.

Depth interviews are commonly used in qualitative research and are suitable for issues that are not easily observed externally or involve fewer research subjects. The participants are usually purposefully selected based on the researcher's understanding of the research purpose and the target population.
While there is no absolute requirement for the sample size in the AHP, it should still meet the two principles of representativeness and richness of obtainable data (Melillo & Pecchia, 2016). The first author of this study works in a lithium battery development, design, and assembly company, serving as the convener and project manager for the introduction of his organization. This positioning placed the author in a unique position to employ purposive sampling in selecting participants. The sampling process involved selecting five smart manufacturing industry experts and five human resource experts from Taiwan's smart manufacturing industry for the questionnaire survey. The aim was to leverage expert opinions and observations to evaluate the key indicators and weights chosen by the researchers through a review of existing literature and industry reports.

**Study design**

The study began with a review of relevant literature and statistical reports from domestic and international sources to elucidate the current state of the smart manufacturing industry. The reviewed data included an occupational competency assessment (Fitzpatrick, 1994; Schmitt & Scheibe, 2023; Spencer & Spencer, 2008), the introduction of smart manufacturing (Ghobakhloo, 2020; Schmitt & Scheibe, 2023; Sjödin et al., 2018; Veza, 2015), organizational innovation strategies (Alharbi et al., 2019; Kotter, 1996; Soomro et al., 2021; Wu & Lin, 2011), future leadership (Čater et al., 2013; Development Dimensions International, 2018; Viitala et al., 2017), key successor development factors (Estedadi & Hamidi, 2015; Ghee et al., 2015; Mehrabani & Mohamad, 2011; Sambrook, 2005), and leadership effectiveness and financial performance (Development Dimensions International, 2018; Koene et al., 2002; Yukl, 2008). Subsequently, a semi-structured expert interview was conducted to construct the AHP framework, which was then used in a structured expert questionnaire to acquire criteria indicators and their priority order. Finally, the AHP method was employed to calculate the relative weights and perform consistency checks. The goal was to elucidate the overall key aspects that small- and medium-sized manufacturing enterprises should consider when introducing smart manufacturing and provide survey results for industry reference, including key weights and priority orders. The decision-makers were required to assess the relative importance of each decision criterion. Based on the feedback of the decision-makers, we assigned a priority order (weights) to each criterion to identify its relative importance in the introduction of smart manufacturing (Saaty, 2008).

Each criterion represented an action strategy for introducing smart manufacturing. Expert opinions were collected using the AHP questionnaire to assess the relative weights of each criterion and determine the priority of each action strategy. In the questionnaire design phase, the first step involved a literature review and semi-structured expert interviews to refine the AHP framework indicators. To minimize issues associated with filling out the questionnaire and maximize questionnaire recovery, we carried out a structured AHP interview survey as the second step. The results of the survey were used to obtain the relative weights between key indicators and rank the action strategies. A relative scale, ranging from equal importance to absolute importance (1 to 9), was used to construct pairwise comparison matrices based on the importance of each design indicator. The priority order of hierarchical elements was then compared by deriving characteristic vectors (Saaty, 1977).

**Questionnaires**

This study aimed to carry out a structured questionnaire survey to summarize potential issues comprehensively for organizations in the future when implementing smart manufacturing and during the organizational innovation process after implementation. Key action strategies for overall smart manufacturing implementation and innovation were proposed based on the survey outcomes. The survey targeted two main categories of participants: smart manufacturing experts and human resource experts. To ensure the practicality, completeness, and appropriateness of the questionnaire, questionnaires were proportionally distributed, specifically, five for the smart manufacturing experts and five for the five human resource experts. Statistical analysis and opinion summarization were carried out after each expert completed the questionnaire. The questionnaire included instructions, motivations and objectives, indicator framework, item structure, and ultimate goals and significance. Each participant was asked to make reasonable judgments and responses regarding the key indicators, which were then used to formulate effective innovation strategies for implementing smart manufacturing.

An AHP reliability analysis was conducted to ensure the reliability and effectiveness of the questionnaire. The AHP uses the consistency ratio (CR) to evaluate the overall consistency of the comparison matrix (Cheng & Li, 2003). The CR is derived from the ratio of the consistency index (CI) to the random index (RI). Saaty (1977) suggested a CR smaller than 0.1 to represent satisfactory matrix consistency. In this study, we performed a CR test for each data set. If the consistency ratio value was greater than 0.1, a violation of the transitive law may have occurred. If a violation was validated in the questionnaire responses, the participant was asked to reconsider the importance of the indicators before comparing them. If a revised response could not be provided, the response was invalidated and excluded from this research (Beissner, 2002). After eliminating the questionnaires with a consistency ratio higher than 0.1, those meeting the criteria underwent further group decision analysis. Using Excel, the geometric mean of each indicator in the remaining questionnaires was calculated (Aguarón & Moreno-Jiménez, 2003; Ishizaka & Labib, 2011; Popp et al., 2019). The values were then input into the Expert Choice software to determine the group weights.

**Results**

In the first stage, we compiled the key indicators associated with the development of smart manufacturing vision and strategies. A total of 33 indicators across six dimensions were identified. In the second stage, semi-structured expert interviews were carried out to revise the indicator framework. The framework was reduced to 27 items across five dimensions (as shown in the appendix). The
hierarchy framework of key indicators for implementing action strategies in smart manufacturing is illustrated in Fig. 1. This framework served as a basis for the prioritization of action weights by the experts. The outcomes were consequently used to formulate the corresponding strategy recommendations.

![Hierarchy Framework of Key Indicators for Implementing Action Strategies in Smart Manufacturing](image)

**Figure 1**: Hierarchy Framework of Key Indicators for Implementing Action Strategies in Smart Manufacturing.

**Analysis results of the key indicators for implementing action strategies in smart manufacturing**

Expert opinions on the relative priority of each element in the second level of the hierarchy framework were obtained from the questionnaires. A comparison matrix of all of the participants is tabulated in Table 1. The relative weights for each of the five key indicators were .320 for occupational competency assessment, .237 for the project planning of smart manufacturing, .189 for innovation strategy changes, .13 for the leadership of managers, and .124 for succession planning and development. The overall CR was .01. The CR of the human resource experts was .03 and that of the smart manufacturing experts was .01. All of the CR values were less than .1, suggesting excellent overall consistency.

<table>
<thead>
<tr>
<th>Key factor</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>Weights</th>
<th>Sorting</th>
</tr>
</thead>
<tbody>
<tr>
<td>A: Occupational competency assessment</td>
<td>1.486</td>
<td>2.318</td>
<td>2.034</td>
<td>1.963</td>
<td>.320</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>B: Project planning of smart manufacturing</td>
<td>1.076</td>
<td>1.902</td>
<td>2.380</td>
<td>.237</td>
<td></td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>C: Innovation strategy changes</td>
<td>1.616</td>
<td>1.616</td>
<td>.189</td>
<td></td>
<td></td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>D: Leadership of managers</td>
<td></td>
<td>1.042</td>
<td>.130</td>
<td></td>
<td></td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>E: Succession planning and development</td>
<td></td>
<td></td>
<td>.124</td>
<td></td>
<td></td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>C.R.=.010</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Differences of the key indicators for implementing action strategies in smart manufacturing among different experts**

Table 2 illustrates the differences in the relative weight perspectives of the smart manufacturing and human resource experts regarding the key indicators of smart manufacturing implementation. The table reveals that there were varying opinions among experts on the critical indicators for the adoption of smart manufacturing. The human resource experts emphasized occupational competency assessment (with a relative weight of .420), followed by innovation strategy changes (with a relative weight of .278). By comparison, the smart manufacturing experts viewed the project planning of smart manufacturing to be the most important (with a relative weight of .293), followed by occupational competency assessment (with a relative weight of .234). These differences stemmed from the distinct viewpoints of the experts when considering the key indicators, leading to the construction of a set of divergent relative weights.
Table 2: Comparison between Human Resource Experts and Smart Manufacturing Experts on the Weights of Main Framework Assessment Indicators.

<table>
<thead>
<tr>
<th>Category</th>
<th>All participants</th>
<th>Human resource experts</th>
<th>Smart manufacturing experts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Weights</td>
<td>Sorting</td>
<td>Weights</td>
</tr>
<tr>
<td>A: Occupational competency assessment</td>
<td>.320</td>
<td>1</td>
<td>.420</td>
</tr>
<tr>
<td>B: Project planning of smart manufacturing</td>
<td>.237</td>
<td>2</td>
<td>.155</td>
</tr>
<tr>
<td>C: Innovation strategy changes</td>
<td>.189</td>
<td>3</td>
<td>.278</td>
</tr>
<tr>
<td>D: Leadership of managers</td>
<td>.130</td>
<td>4</td>
<td>.070</td>
</tr>
<tr>
<td>E: Succession planning and development</td>
<td>.124</td>
<td>5</td>
<td>.077</td>
</tr>
<tr>
<td>C.R.</td>
<td>.010</td>
<td></td>
<td>.030</td>
</tr>
</tbody>
</table>

Table 3 shows that at the third level of the framework, motivation (A5) was the most crucial key indicator (relative weight of .143), followed by cognition of differences between Industry 4.0 and automation (B1; relative weight of .086). However, there were differences of opinion between the human resource and smart manufacturing experts. The human resource experts considered motivation (A5) to be the most important key indicator (relative weight of .211), followed by self-traits (A4; relative weight of .078), suggesting that from a human resource perspective, emphasizing the foundation of occupational competency assessment (Key Factor A) is essential in driving the implementation of smart manufacturing. Conversely, for the smart manufacturing experts, the cognition of differences between Industry 4.0 and automation (B1) was the key indicator (relative weight of .094), followed by motivation (A5; relative weight of .093). The discrepancies stemmed from the fact that different professional roles prioritize different aspects of smart manufacturing according to their duties and responsibilities. Therefore, when undergoing organizational change through the implementation of smart manufacturing, it is imperative to balance perspectives from different roles and identify the most appropriate execution strategy.

Table 3: Differences in the Top Five Action Strategies at the Sub-Indicator Level between Human Resource Experts and Smart Manufacturing Experts.

<table>
<thead>
<tr>
<th>All experts</th>
<th>Human resource experts</th>
<th>Smart manufacturing experts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Item</td>
<td>Weights</td>
<td>Sorting</td>
</tr>
<tr>
<td>Motivation</td>
<td>.143</td>
<td>1</td>
</tr>
<tr>
<td>Cognition of differences between Industry 4.0 and automation</td>
<td>.086</td>
<td>2</td>
</tr>
<tr>
<td>Recommended steps for smart manufacturing literature data integration</td>
<td>.068</td>
<td>3</td>
</tr>
<tr>
<td>Self-traits</td>
<td>.060</td>
<td>4</td>
</tr>
<tr>
<td>High potential for continuous learning</td>
<td>.054</td>
<td>5</td>
</tr>
</tbody>
</table>
Discussion

In today's highly competitive environment, reducing cost-related losses during organizational restructuring has become a crucial operational issue (Cascio, 2005). Particularly, organizational transformation is imperative in response to the organizational changes brought about by the implementation of smart manufacturing in Industry 4.0. Subsequently, talent is considered a core component of organizational change (Recardro & Heather, 2013). Therefore, transforming talent into a valuable asset for the organization should be the focus of organizations seeking transformation (Gardner, 2005). When reforming innovation strategies, a well-thought-out set of action strategies must be devised to minimize the loss of talent and capital, foster mutual growth within the organization, and achieve win-win outcomes and sustainable organizational growth. This study focused on the key action strategies in the process of smart manufacturing implementation. We aimed to identify the critical factors of transformation based on the current status of industry transformation and create opportunities for sustainable business. The dimensions and indicators of the action strategies identified in this study are discussed in the following sections.

The constructs of action strategies

After consolidating the opinions of the interviewed experts, we found that occupational competency assessment (Key Factor A) was perceived as the primary factor influencing the key indicators. This is because human resource management plays a crucial role in the success of the organizational change process (Costanza et al., 2016). Therefore, regardless of the project, organizations must comprehensively assess the differences in employees' competency to facilitate the execution and planning of the projects, thereby accelerating the development of the organization's long-term strategic goals (Fugate, 2013). This is particularly true in terms of the implementation of smart manufacturing. Fahmy et al. (2022) asserted that specific skills and attitudes are required for organizational digital transformation, whereby the attitude, culture, and digital literacy of the talent assigned to related projects significantly affect the speed of transformation (Fahmy et al., 2020). Frankiewicz and Chamorro-Premuzic (2020) argued that in the digital transformation process, the primary focus should be on talent rather than technology. This argument was validated in this study. As expected, the human resource experts, responsible for organizational talent deployment, highly valued occupational competency assessment (Key Factor A) during the transformation stage. Surprisingly, the smart manufacturing experts, who prioritized the project planning of smart manufacturing (Key Factor B), also highly valued occupational competency assessment (Key Factor A), reiterating the importance of talent quality in organizational change. In practice, competency gap analyses and human resource development strategies can be utilized to enhance future talent development and the organization's core competitiveness (Gannon et al., 2012).

Moreover, we observed a close relationship between the project planning of smart manufacturing (Key Factor B), which was highly valued by the smart manufacturing experts, and human resource management. Key Factor B emphasized the awareness of Industry 4.0, where cognition plays a crucial role in the rational processing of information and the creation of a conceptual world (Yuan, 2005). Only through the cognitive adjustment of employees within the organization can the project planning of smart manufacturing be initiated. This relationship also highlighted the pivotal role that key talent plays in the core competitiveness of the organization in a globally competitive environment. However, despite the general desire for talents to contribute immediately to the organization's success in initiating projects or strategies of organizational change, a survey by the National Development Council of Taiwan revealed that the insufficient supply of graduates is a significant reason for talent shortages (National Development Council, 2021). To address this issue, it is necessary to identify which key behaviors during the organizational change process can effectively enhance organizational performance and then select the most suitable candidates from the existing talent with these behaviors, thereby assigning the right people to the right positions and reducing personnel costs during project implementation. Since talent cultivation in smart manufacturing is the fundamental solution to talent shortages (Zhang et al., 2023), national policies need to be constantly updated to ensure that talent cultivation policies are in line with industry demand. This should also be a key focus of the education industry in Taiwan.

The indicators of action strategies

We consolidated the expert opinions regarding the 27 indicators at the sub-indicator level and found that motivation was the most valued. According to the Job Demands–Resources Theory, factors facilitating successful change include the motivation structure, which encompasses organizational resources, job resources, job demands, and personal resources. Subsequently, these resources may be associated with employees' engagement in the change process (Albrecht et al., 2020). Motivation, being one of the driving forces for action, is a crucial psychological factor in sustaining behavior (Pak et al., 2019; Renard & Snelgar, 2018) and necessary for achieving set goals. In other words, motivation is a precursor to behavior (Renard & Snelgar, 2018). This is, therefore, the reason why the experts considered motivation to be the most important key factor in organizational change.

Cognition of differences between Industry 4.0 and automation was the second most valued sub-indicator by the experts. As mentioned earlier, this action strategy indicator is a factor involving an individual's internal cognition. In the context of this study, it represented employees' views of Industry 4.0. Similar to motivation, if the barriers of internal cognition cannot be overcome, it may hinder the progress of implementing smart manufacturing.

According to the responses of the human resource experts, the first five action strategy indicators all involved human resource thinking. Apart from the four indicators related to individual behaviors and internal thinking at the employee level, the active participation of senior managers, which ranked third overall, was also highlighted as an important indicator, suggesting that the
behavior and willingness of supervisors are crucial factors influencing the success of organizational change (Luo et al., 2020). The results, therefore, indicated that human resource managers find the perspectives and willingness of employees and supervisors to be the most important aspects affecting organizational change.

The viewpoint of the smart manufacturing experts was somewhat different. Apart from motivation and the cognition of differences between Industry 4.0 and automation, the other three most valued action strategy indicators were associated with the implementation. These outcomes were reasonable given the experts’ background in smart manufacturing and their concerns about whether the implementation of smart manufacturing can effectively achieve organizational goals. Therefore, the experts believed that recommended steps for smart manufacturing literature data integration, training and development, and high potential for continuous learning were crucial for the success of smart manufacturing implementation. Furthermore, the responses of the smart manufacturing experts also highlighted their emphasis on talent development. Unlike the human resource experts, the smart manufacturing experts focused more on cultivating executive skills to cope with the rise of artificial intelligence (AI) (Wanous et al., 2000).

In preparation for a turbulent future, organizations should prioritize talent management and development and combine human resource development strategies with organizational innovation/change strategies (Albrecht et al., 2020). Implementing smart manufacturing to achieve organizational innovation requires suitable talent and strategy formulation mechanisms to ensure that goals are clearly defined and that action plans are effectively carried out (Chen et al., 2023).

Conclusions

As environment uncertainty increases, organizations are faced with the two-pronged issue of accelerating organizational change and ensuring the success of organizational change. Researchers need to understand further the factors that contribute to the success of driving change. This study took the key action strategies of smart manufacturing implementation as a starting point to explore the critical factors of organizational change in the digital era. The results clearly highlighted the importance of employee thinking and talent development. Additionally, the key indicators of organizational change proposed in this study can be used by organizations to measure the likelihood of change. The proposed model was validated to be an effective tool in helping organizations effectively allocate organizational resources and promote organizational change. Organizations with the resources and capacity for change can utilize the proposed model to address the challenges and opportunities of ongoing organizational change.

Limitations

In the AHP, the indicators were selected solely based on expert suggestions. An objective statistical method was not employed to analyze the correlation among employees. This was the primary limitation of this study. Future researchers can build on the research foundation established in this study and use objective data for indicator validation. Additionally, they can consider incorporating different theoretical perspectives to explore new normal organizational phenomena, taking into account the impacts at the individual, organizational, and macro levels. We hope that this study inspires researchers to explore job motivation and behavior further in the current new normal environment.

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References


Appendix: Key indicators for implementing smart manufacturing action strategies

1. Key factor A: Occupational competency assessment
   - A1: Skills (executive ability)
   - A2: Knowledge (professional)
   - A3: Self-concept (self-perception)
   - A4: Self-traits
   - A5: Motivation

2. Key factor B: Project planning of smart manufacturing
   - B1: Cognition of differences between Industry 4.0 and automation
   - B2: Recommended steps for smart manufacturing literature data integration
   - B3: Checklist of goal setting and planning
   - B4: Checklist of smartization level evaluation

3. Key factor C: Innovation strategy changes
   - C1: Establishing crisis awareness
   - C2: Active participation of senior managers
   - C3: Formulating a clear vision and strategies
   - C4: Building consensus
   - C5: Executing a shared vision
   - C6: Establishing reward mechanisms
   - C7: Continuously updating and adjusting
   - C8: Solidifying change behaviors

4. Key factor D: Leadership of managers
   - D1: Digital leadership capability
   - D2: Learning adaptability
   - D3: Action execution ability
   - D4: Highly international collaboration
   - D5: Identifying and cultivating future talent
   - D6: 360° global perspective

5. Key factor E: Succession planning and development
   - E1: Talent management
   - E2: Performance management
   - E3: Training and development
   - E4: High potential for continuous learning

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