Decoding Enterprise Investment Drivers in Industry 4.0 Smart Manufacturing

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Abstract

Industry 4.0, integrating smart manufacturing, digital manufacturing, smart logistics, and industrial automation, has emerged as a core paradigm for industry leaders and scholars advancing sustainable development. This study develops a theoretical model to decode the key drivers influencing enterprises' intentions to invest in smart manufacturing. The model was empirically analyzed using data from an online survey of 188 R&D and project development professionals from manufacturing and high-tech enterprises in Taiwan. The findings unveil critical insights into sustainable investment strategies for Industry 4.0, offering practical guidance for policymakers, industry stakeholders, and researchers, while paving the way for the future evolution of smart manufacturing.

Keywords: Industry 4.0; Smart Manufacturing; Industrial applications of the Internet of Things; Industrial Internet; Social Cognitive Theory; Government Subsidy Policies; Investment Intention

1. Introduction

The innovation and sustainable developments of the continued miniaturization of Information and Communication Technology (ICT), and Cyber Physical Systems (CPS) in recent years have driven dramatic changes in industrial manufacturing models, technologies, and value chains. The sensor technologies and actuators are usually recognized as core technologies [1].

In countries with strong manufacturing industries, the correlation effects of productivity of those industries are much higher than those generated from service industries, prompting the need to aggressively create a new wave of revival and revolution in manufacturing industries. Germany, well known for its manufacturing industry, took the lead in coining the term「Industrie 4.0」 (Industry 4.0) in 2011 at the Hannover Industrial Fair and pointed out a new direction for global manufacturing industries [2].

Industry 4.0 focuses on the integration of ICT hardware and CPS software. Industry 4.0 is expected to enhance a range of current key manufacturing conditions, such as costs, productivity, quality, and flexibility, thus accelerating technology convergence and will significantly affect the way people live in various respects.

Each advanced country pursues smart manufacturing industry development initiatives which suit their economic priorities. The United States is pursuing an Advanced Manufacturing Partnership (AMP) seeking to revitalize the country's manufacturing base by upgrading manufacturing capacity and luring manufacturers back as a means of generating more jobs. Japan, with its deep strengths in industrial automation, is promoting Japan Industry 4.1J, which seeks to further extend the use of industrial robots to compensate for the country's increasingly acute labor shortage due to its aging society. South Korea is promoting Industry Innovation 3.0 which targets economic restructuring, promote innovation and balance industrial imports and exports. China has initiated a Made in China 2025 (MIC 2025) plan which will transform China into a global leader in advanced manufacturing, set to surpass both Germany and Japan by 2035 [3].

Taiwan is a key player in the global information technology (IT) marketAdditionally, Taiwan is also a major supplier of high-end components for global tech leaders such as Apple, Microsoft, and Intel. The Taiwan government's industrial development policy is a key factor underpinning this performance. In late 2015, the government launched the Taiwan Productivity 4.0 initiative to drive a new industrial revolution that shift manufacturers from automated to intelligent production. Moreover, this initiative transforms Taiwan from an efficiency driven economy to an innovation driven economy. Productivity 4.0 integrates the concepts of intelligent machinery, Internet of Things (IoT) technology, and big data applications. The initiative, running from 2015 through 2024, will inject NT$36 billion (US$1.13 billion) into the manufacturing, commercial service, and agricultural sectors [4].

According to a 2016 PricewaterhouseCoopers (PwC) survey, the successful implementation of Industry 4.0 initiatives will increase annual revenues and reduce cost by an average of 2.9% and 3.6% respectively. Moreover, global in dustrial product companies intend to make annual investments averaging US$907 billion through 2020. This investment is primarily directed to digital technologies like sensors or connectivity devices, as well as software and applications like Manufacturing Execution Systems (MES). Also, a 2014 analysis by Gartner Inc. predicted that, by 2020, the IoT market will grow to more than 26 billion devices (excluding PCs, tablets, and smartphones), producing annual revenues of over $300 billion, mostly through the provision of IoT services.

The industrial sector has started to shift towards a novel paradigm that emphasizes sustainable Industry 4.0. In the range of technology, the Internet of Things, cloud computing, big data analysis, artificial intelligence, augmented and virtual reality, collaborative and cognitive robotics, computer modeling and simulations, additive manufacturing have became the concept of concerns[5].

Each country varies in its industrial conditions and how it is proceeding to promote and implement concepts and practices. Industry 4.0 represents a revolution in engineering which integrates a wide range of industrial and technological fields. It is worth underline that social and economic aspects are very significant in Industry 4.0 on sustainability [6]. This research reviews and analyzes the global literature on Industry 4.0, using Social Cognitive Theory (SCT) to examine the current status of Taiwan's manufacturing industry market and to develop a model which can be used to identify key factors that impact firm intention to invest in smart manufacturing.

This research will discuss whether and how an enterprise's intention to invest in Industry 4.0 initiatives is affected by market maturity and government policies. Constructs considered as potential impact factors include perceived demand market maturity, perceived supply market maturity, government subsidy policies, self-efficacy, and outcome expectancy. This research provides concrete advice on the development of smart manufacturing to consider sustainability issues. A framework is also proposed for further study of Industry 4.0 for government, academia, and research institutes.

2. Literature Review

2.1. Subsection Industry 4.0

The first industrial revolution (Industry 1.0) started at the end of the 18th century through the introduction of machine based production facilities while the second industrial revolution (Industry 2.0) took place 30 years later involved the development of mass production systems powered by electricity. The first assembly line was built in 1870, launching the era of mass production. The third industrial revolution (Industry 3.0) began in the early 1970s with the development of the first programmable logistic control system, leading to production automation based on electronic and IT systems. The fourth industrial revolution (Industry 4.0) is currently underway, using of Cyber Physical Systems (CPS) which are integrated throughout entire production processes by merging real and virtual worlds through hyper connected IoT devices and IT systems. Machines and robotics are controlled by automated systems equipped with sensor technology, machine learning algorithms, and artificial intelligence, thus requiring minimal input from human operators [7].

National Institute of Standards and Technology (NIST) defines smart manufacturing as fully integrated and collaborative manufacturing systems that respond in realtime to meet changing conditions in production facilities and supply networksas well as changing customer needs [8]. In other words, smart manufacturing is a proactive manufacturing technology capable of reacting to complex and diverse conditions and scenarios in realtime. Radziwon [9]defined smart factories as a manufacturing solution that provides flexible and adaptive production processes to solve production problems in factories characterized by dynamic and rapid changing boundary conditions. These solutions could focus on automation through the integration of software, hardware, and/or mechanics to optimize manufacturing processes and thus reduce labor and resource costs. It could be seen from a perspective of collaboration between various industrial and nonindustrial partners, where the system intelligence is provided from the formation of dynamic organizations. Industry 4.0 can thus offer productivity gains as a result of technological advancement that leads to the improvement of human-human, human-machine, and machine-machine collaboration [7].

In their comprehensive literature review on past and present trends in smart manufacturing, Kang et al [10] mentioned five key technologies including networked sensors, data interoperability, multiscale dynamic modeling and simulation, intelligent automation, and scalable and multilevel cybersecurity. They also summarized policies and research trends in advanced manufacturing countries (e.g., Germany, U.S., etc.), with predictions of future developments.

Chen and Tsai [11] identified features of ubiquitous manufacturing (UM) as being “design anywhere, make anywhere, sell anywhere, and at any time.” They introduced UM systems and technologies, reviewed current UM practices, discussed the challenges faced by researchers and practitioners, and identified potential opportunities for UM development shortly. They revealed that the success of UM depends on the quality of manufacturing services deployed and that UM is a realizable target for Industry 4.0.

Other recent studies related to Industry 4.0 include [12] using applied big data analysis methods to the Industry 4.0 context, devising an approach integrating heterogeneous data sources to enable automated risk assessment. Stock and Seliger [13] presented a state of the art review of Industry 4.0 based on recent developments in research and practice, followed by an overview of different opportunities for sustainable manufacturing in the Industry 4.0 context. Foidl and Felderer [14] identified upcoming challenges and opportunities in the quality management domain given Industry 4.0 developments.

2.2. Industry 4.0 Social Cognitive Theory

Developed by [15,16], Social Cognitive Theory (SCT) is a widely accepted model for validating individual behavior and has been used as the basis of many different types of the research framework. In the SCT model, behavior, and environmental influence, along with cognitive and other personal factors act as interacting determinants which influence each other bidirectionally. Thus, SCT seeks to analyze how thoughts, feelings, and social interactions shape individual behavior and has been widely used in education, psychology, and ICT usage [17-22].

2.2.1. Self-efficacy

In SCT, self-efficacy is an important cognitive factor that drives human behavior. Defined as “the belief in one’s capabilities to organize and execute a course of action that is required to manage prospective situations” [15]. Self-efficacy reflects the degree of a person’s belief in his or her ability to succeed in a particular situation or executing a behavior, rather than a person’s actual proficiency in specific skills. In conclusion, individuals who have high self-efficacy will be more likely to attempt related behavior than those with low self-efficacy [21].

In prior studies, self-efficacy has been used to help understand individual knowledge sharing motivations and be-haviors in social media platforms and virtual communities. Ifinedo [23] investigated factors influencing undergraduate students’ continuance intention to use blogs for learning, found that perceived self-efficacy, personal outcome expectations, and perceived support for enhancing social ties are the key antecedents to initial acceptance of blog use for learning. Kwahk and Park [24] empirically proved that knowledge self-efficacy, social interaction ties, and the norm of reciprocity positively influence knowledge sharing activities in social media, which in turn influences individual job performance. Chen, et al., [25] demonstrated that self-efficacy and organizational climate have positive effects on knowledge sharing behavior within enterprise social media environments.

Self-efficacy also used by many IS scholars in a variety of research streams, including examining the effect of self-efficacy on an individual’s use of information technology. Indeed, Internet self-efficacy has been positively linked to attitudes toward computer use [26,27] as well as social networking sites [20]. Compeau and Higgins [17] revealed that an individual's self-efficacy and outcome expectations play an important role in shaping that individual’s feelings and behaviors. Individuals with high self-efficacy used computers more frequently and derived more enjoyment from such use. Khang et al., [28] explored the impact of self-efficacy as a significant antecedent of an individual’s perspective behavior for using new media formats. Self-efficacy has also been found to be important for developing digital competence [29,30].

2.2.2 Outcome expectancy

Based on the SCT, in addition to self-efficacy, the concept of outcome expectancy is another key construct [31]. Outcome expectancy is defined as how “individuals can believe that a particular course of action will produce certain outcomes, but if individuals entertain serious doubts about whether they can perform the necessary activities, such information does not influence their behavior,” [15]. People are more likely to engage in a given action if they expect their actions will yield some reward or benefit [17].

In the contexts of innovation and new product development, innovation outcome expectancies are defined as beliefs about the consequences of enacting specific working behaviors aimed towards fostering innovation [32-34]. Cingöz and Akdogan [35] investigated factors influencing employees’ innovative behavior, and reported that expected performance outcomes are positive when employees believe that their innovative behavior will obtain some personal professional image and obtain performance improvements for their work role or work unit.

Moghavvemi et al., [36] found that outcome expectancy is the main factor affecting students’ intention to share knowledge over social media. Students’ willingness to share knowledge and help others was a function of their expectation of receiving respect, recognition, and favorable feedback from peers, along with the opportunity to enrich their knowledge. Niederhauser and Perkmen [37] revealed that, concerning integrating technology into teaching practice, outcome expectancy is a multifaceted construct consisting of three expectancy components: i.e. performance, self evaluation, and social outcome.

ISSN: 0067-3064

3. Research model and hypotheses

Our research model was based on this review of the relevant literatures. Using SCT as a framework, the model developed in this research focuses on the current status of manufacturing in Taiwan and concerns about the impact factors of enterprise intention to invest in smart manufacturing. The theoretical structure is developed and explained in this chapter. A questionnaire was distributed over the Internet for evaluation constructs and model validation. The collected responses of the survey were processed through data analysis tools for model validation and hypotheses testing.

This research, based on SCT, will discuss how the constructs affect enterprise intention to invest in smart manufacturing. Comparing our research model with SCT, perceived demand market maturity, perceived supply market maturity, and government subsidy policies could be viewed as environmental factors, while self-efficacy and outcome expectancy are organizational factors and investment intention is a behavioral factor. According to SCT, personal factors (organizational factors in our study) are influenced by environmental factors, while behavioral factors are influenced by personal factors (organizational factors in our study). The research model is depicted in Fig. 1.

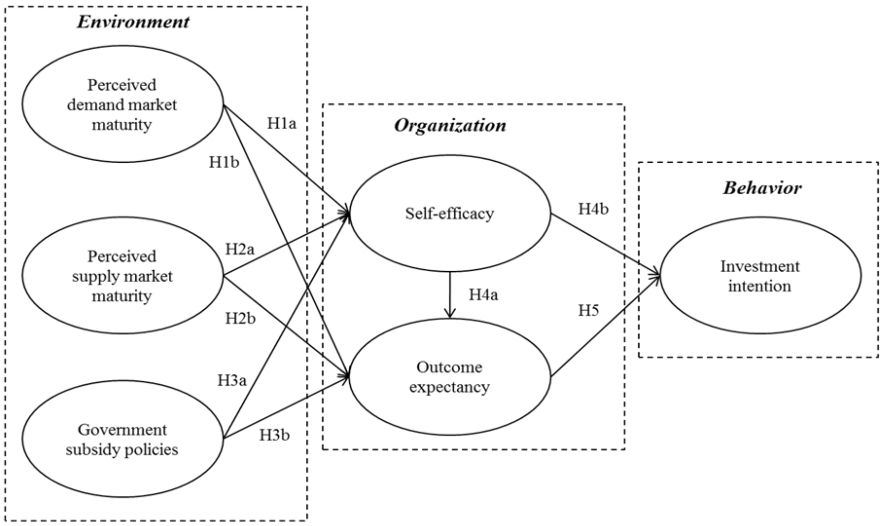


Fig. 1. Research model

3.1. Perceived demand market maturity

Market demand is a key impact factor for enterprise innovation and new product development [38,39]. Slater and Narver [40] suggest that enterprise success depends on a timely response to a gap between the demand and supply. Therefore, innovation has emerged as the key mechanism by which manufacturing firms seek to grow market share [41,42]. Lin et al. [43] found a positive correlation between market demand, green product innovation, and enterprise performance, suggesting that firms must emphasize familiarity with the requirements of their target customers and seek to anticipate changes in customer preferences to stay ahead of market demand and thus improve competitive advantage. Good innovation performance will help firms improve their market positions and acquire new customers [44]. In summary, this research proposes the following hypotheses:

【H1a】perceived demand market maturity has a positive effect on self-efficacy

【H1b】perceived demand market maturity has a positive effect on outcome expectancy

3.2. Perceived supply market maturity

Enterprises and governments both encourage innovation for the creation of market and social benefits. Several studies have examined various aspects of supply markets, such as sustainable procurement [45], sustainable supply chain management [46], public procurement used as an innovation policy to stimulate private sector innovation [47]. Most such studies focus on high-tech products and find a high degree of interdependency between demand and suppliers' supply capability [48]. Moreover, intense competition also reflects the product or service provision under market pressure [49]. Thus the following hypotheses are proposed:

【H2a】perceived supply market maturity has a positive effect on self-efficacy

【H2b】perceived supply market maturity has a positive effect on outcome expectancy

3.3 Government subsidy policies

Science and technology development and upgrading are widely seen as the main sources to power continuous economic growth, underlining the importance of research and development (R&D). Many previous studies have indicated that government policy plays an important role in assisting firms to innovate, and thus enhance their competitiveness by introducing new products or services and by generating opportunities for useful collaboration [50,51]. Hsu et al., [52] surveyed 127 government funded projects in Taiwan, found that government R&D funding alters the behavior of recipient firms and affects their propensity for innovation.

Governments seek to promote innovation through offering financial subsidies and patent protection [53]. Other mechanisms include favorable tax treatment, stimulus loans, and government funding projects [54-56]. Doh and Kim [57] found that support from the South Korean government had a positive impact on innovation by small and mediumsized enterprises (SME). In the context of the German manufacturing industry, Hussinger [58] found that government subsidies and private financing positively impacted enterprise patent development. Reischauer [59] suggested that Industry 4.0 be seen as a policy driven discourse that aims to promote innovation. Accordingly, this research proposes the following hypotheses:

【H3a】government subsidies have a positive effect on self-efficacy

【H3b】government subsidies have a positive effect on outcome expectancy

3.4 Self-efficacy

Self-efficacy is related to one's ability to become aware of one's motivation, perceive resources, and effectively manage events and processes. When a person considers him/herself capable of achieving something, he/she has high self-efficacy and greater willingness to undertake the goal. Compeau et al., [18] found self-efficacy to be explanatory in models of individual reactions to computing technologies. Self-efficacy has been widely shown to be a major impact factor on attitudes and beliefs related to various technologies [60,61]. Such beliefs could potentially drive enterprises' intention to use and invest in smart manufacturing. Other studies have shown that perceived self-efficacy positively affects outcome expectancy way [17,18]. Accordingly, the following hypotheses are proposed:

【H4a】self-efficacy has a positive effect on outcome expectancy

【H4b】self-efficacy has a positive effect on investment intention

3.5 Outcome expectancy

Outcome expectancy is also an important facet to explain and predict personal behavior. A rational person will only undertake a task under the expectation of certain results [62]. Expectancy helps a person to form his/her cognition map and internal plan to achieve a goal [63]. Outcome expectancy is also widely used in career related activities and has been shown to be an important factor [64-66]. Yuan and Woodman [67] discussed how outcome expectancy influences innovation behavior among individual employees to drive organizational success. A belief that the outcome of innovation behavior would improve their work role and organization performance has a positive impact on productivity, work quality, error rates, and capability to meet targets. Accordingly, the following hypothesis is proposed:

【H5】Outcome expectancy has a positive effect on investment intention

4. Research methods

4.1 Data collection and Demographics

All proposed hypotheses were empirically tested using a survey of professionals from R&D departments or innovation project teams in manufacturing and high-tech firms in Taiwan. A group of nine managers and supervisors from these firms were recruited to promote our web-based questionnaire among their R&D staff. Researchers have suggested that online surveys have several advantages over traditional paper-based surveys including being less expensive, eliciting faster responses, and not being subject to geographic restrictions [68,69].

During the four-week survey period, 193 responses were received, of which five were excluded for incompleteness. Of the remaining 188 valid respondents, 88 had 1-3 years of working experience, while the remaining 100 had four or more years of working experience (4-6 years: 27, 7-9 years: 18, above 10 years: 55). Enterprises with a market capitalization exceeding USD 31 million accounted for 58.5% of respondents. Most of the respondents (138 respondents, 73.4%) worked for smart manufacturing equipment or technology suppliers; 19.1% were from smart manufacturing equipment or technology users; the rest are other types of manufacturing firms. More than half of respondents (56.3%) indicated some knowledge of government subsidy policies to promote development in their industry.

4.2 Research instrument

Most of the questions in the survey were adapted or modified from past research papers [70,71]. Some items were self-developed and were first examined by two marketing experts to ensure a good fit with the context of our study (see Appendix A). All items were measured on a five-point Likert scale ranging from ‘‘strongly disagree’’ (1) to ‘‘strongly agree’’ (5).

4.3 Analysis

A two-step approach was adopted. The first step tested the reliability and validity of the measurement model. The second step assessed the research hypotheses and structural model using partial least squares (PLS). PLS was selected due to it is suitable for small sample research and places minimal demands on measurement scales and residual distributions [72].

5. Results

5.1 Tests of the measurement model

The reliability analysis used Cronbach's composite reliability (CR) to assess the model's internal consistency. Table 1 provides details of these results. The Cronbach's alpha value of each construct ranged from 0.75 to 0.92, all exceeding 0.7 as recommended [73]. Each CR scored above 0.80, exceeding the 0.7 scores suggested for CRs [74]. Convergent validity is established according to the three standards recommended [75]. All indicator factor loadings should exceed 0.5 [73]; the CR should be above 0.7, and the average variance extracted (AVE) should exceed 0.5 [74]. The indicator factor loading of each item exceeds 0.7. The CR ranges from 0.85 to 0.95. The AVE ranges from 0.66 to 0.87. The discriminant validity was assessed by the square root of the AVE for each construct, which should be greater than the correlation among the constructs [74]. Table 2 shows that all square roots of the AVE (diagonal numbers) are greater than the off-diagonal numbers. Therefore, the measurement model shows satisfactory reliability, convergent validity, and discriminant validity.

Table 1. Summary of measurement scales

	Items	FL	CR	AVE	Mean	α
Perceived Demand Market Maturity (DMM)	DMM 1 DMM 2 DMM 3	0.87 0.76 0.81	0.85	0.66	3.46	0.75
Perceived Supply Market Maturity (SMM)	SMM 1 SMM 2 SMM 3	0.90 0.88 0.91	0.93	0.80	2.93	0.88
Government Subsidy Policies (GSP)	GSP 1 GSP 2 GSP 3	0.95 0.93 0.91	0.95	0.87	2.86	0.92
Self-Efficacy (SE)	SE 1 SE 2 SE 3 SE 4 SE 5	0.85 0.89 0.88 0.90 0.86	0.94	0.77	3.05	0.92
Outcome Expectancy (OE)	OE 1 OE 2 OE 3	0.91 0.93 0.91	0.63	0.50	3.20	0.73
Investment Intention (II)	II 1 II 2 II 3	0.90 0.89 0.90	0.92	0.80	3.58	0.88

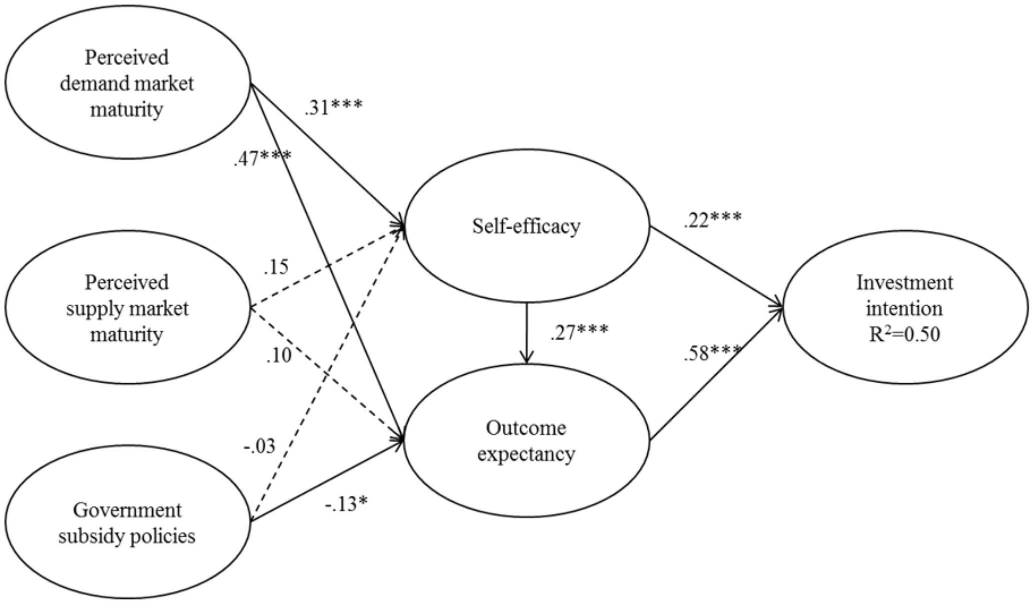
Note: FL (Factor loadings)；CR (Composite reliability)；AVE (Average variance extracted)；SD (Standard deviation)； α (Cronbach's α).

Table 2. Discriminant validity

Construct	DMM	SMM	GSP	SE	OE	II
DMM	0.81					
SMM	0.30	0.89				
GSP	0.27	0.31	0.93			
SE	0.35	0.28	0.14	0.88		
OE	0.56	0.27	0.03	0.45	0.86	
II	0.54	0.19	0.01	0.51	0.69	0.89

5.2 Tests of the structural model

The structural model was tested using structural equation modeling. The estimations result from PLS are shown in Fig. 2. Bootstrap resampling was applied to determine the significance of the structural model paths. The path coefficient among the constructs and the significance of each hypothesis were examined. The empirical test results indicate that six out of the nine hypothesized relationships in our model were significant. First, the testing results support the influence of perceived demand market maturity on self-efficacy (β=0.31, $p<0.001$), and outcome expectancy (β=0.47, $p<0.001$), thus supporting H1a and H1b. The hypothesized path from government subsidy policies is negatively related to outcome expectancy (β=-0.13, $p<0.05$), thus H3b is not supported. The hypothesized path from self-efficacy is significant in the prediction of outcome expectancy (β=0.27, $p<0.001$) and on willingness to invest in smart manufacturing (β=0.22, $p<0.001$), supporting H4a and H4b. The effect of outcome expectancy on willingness to invest in smart manufacturing is significant (β=0.58, $p<0.001$), supporting H5. As hypothesized, most paths were positively significant at the $p<0.05$ level or above. However, perceived supply market maturity did not have a significant direct effect on self-efficacy or outcome expectancy, thus H2a and H2b were not supported. In addition, government subsidy policies did not have a significant direct effect on self-efficacy, thus H3a was not supported. The explained variation (R2) indicated how well the antecedents explained the endogenous variables. With an explanatory power of 50 percent, the willingness to invest in smart manufacturing is influenced by self-efficacy and outcome expectancy.



<0.01; *** p<0.001.

Fig. 2. Results of structure model

6. Conclusion and discussion

Recently, sustainable development in industry 4.0 has emerged as a key topic of discussion in companies, universities, and research centers. This paper sheds light on why firms decide to invest in smart manufacturing, developing an integrated theoretical framework to identify important antecedents to such decisions. The findings reveal that perceived demand market maturity is the most important factor, showing a strong positive influence on self-efficacy and outcome expectancy. In addition, self-efficacy and outcome expectancy both play critical roles in enterprises’ willingness to invest in smart manufacturing for sustainable development. However, perceived supply market maturity does not have a significant direct effect on self-efficacy or outcome expectancy. Moreover, government subsidy policies exert a negative influence on outcome expectancy. A more detailed discussion follows.

First, our results reveal that perceived demand market maturity positively influences self-efficacy and outcome expectancy. This is consistent with previous research suggesting that market demand is a critical factor in the business environment and can be seen as a driving force behind the creation of products to meet customer and market needs [76]. It also supports research evidence showing that firms need to develop innovative manufacturing processes, products, and services to satisfy customer demand as well as government regulations [77]. Moreover, the efforts undertaken to address environmental concerns are largely driven by market demand [78]. Most of the samples in this research were collected from smart manufacturing equipment or technology suppliers and are thus more concerned with market demand than supply.

Second, the Taiwan government has formulated appropriate industrial policies to cultivate high technology industries [52]. However, somewhat surprisingly, our results find government subsidy support had a negative impact on self-efficacy and outcome expectancy. Görg and Strobl [79] found that government grants may completely crowd out private R&D spending, and cast a negative effect on the firm’s innovation. In addition, public subsidies stimulate business R&D through small grants, but large grants can crowd out business R&D. Hong et al. [80] also found that government grants exert a negative influence on innovation efficiency in high-tech industries. Furthermore, according to the statistical analysis data, government subsidy policies are positively correlated with self-efficacy and outcome expectancy, but multivariate analysis shows a negative effect instead. This can be seen as a result of small interference during the statistical analysis.

The third finding from our empirical study is that perceived supply market maturity did not have a significant direct effect on self-efficacy or outcome expectancy. This could be explained by the average point of perceived supply market maturity being just 2.93. In addition, most of the samples were taken from smart manufacturing equipment or technology suppliers who sell smart manufacturingrelated equipment and technology to other companies. Thus, they are more concerned with demand market maturity than supply market maturity which, in turn, results in a non-significant effect of perceived supply market maturity on self-efficacy and outcome expectancy.

The fourth finding is the pivotal roles played by self-efficacy and outcome expectancy: Both have a significant effect on willingness to invest in smart manufacturing. Self-efficacy has been found to be an important determinant to predict people’s behavior [60,81]. In this study, perceived demand market maturity had a significant and direct effect on self-efficacy. However, our findings indicated that perceived supply market maturity and government subsidy policies do not dominate self-efficacy. The results showed that outcome expectancy also had stronger effects on behavioral intention. Enterprises may invest in smart manufacturing when they expect that doing so will increase revenue. In addition, perceived demand market maturity and self-efficacy played critical roles in determining outcome expectancy and explained about 39 percent of the variance for that construct. These results support previous findings indicating that innovation performance is significantly influenced by innovation self-efficacy and innovation outcome expectancy [21]. It is also consistent with previous findings that employees are more likely to engage in innovative behavior when they expect such behavior will benefit their work through increased productivity, increased efficiency, reduced error rate, and improved general job performance [35,67].

7. Implications and limitations

From a theoretical standpoint, the findings of this study provide three contributions. First, the literature review shows that academic research related to Industry 4.0 consists mostly of descriptions and summaries of current status and future trends in various countries, while the development of theoretical framework research models and empirical studies are still rare. This research used the social cognitive theory as its theoretical base and developed a model of proposed impact factors for enterprise intention to invest in smart manufacturing.

Second, unlike previous studies that adopted social cognitive theory for validating individual behavior, this paper adopts an organizational viewpoint to examine enterprise actions to address the business environment. The proposed theoretical research model could serve as a reference for future works in the discussion of Industry 4.0 and quantitative research in smart manufacturing.

Third, a social cognitive theory has proven helpful to understanding people’s performance in knowledge sharing (e.g., [23]), social media use (e.g., [28]) and working (e.g., [82]). To our best understanding, a social cognitive theory has seldom been used to investigate a firm's willingness to invest in smart manufacturing. As such, this study fills a research gap by building a social cognitive theoretical model of perceived market maturity, government subsidy policies, and willingness to invest in Industry 4.0.

The integration of advanced technological factors—such as cloud computing, robotics, big data, the Internet of Things (IoT), and Large Language Models (LLMs)—tailored to specific purposes and user groups presents a significant challenge. Effectively addressing this challenge can substantially improve the usability of AI systems in smart manufacturing, promoting a more human centric approach to understanding and interacting with AI technologies. Globally, enterprises are striving to establish a new ecosystem for the manufacturing sector, facilitating the transition and advancement toward smart manufacturing [83].

Furthermore, this research found that government subsidy policies and perceived supply market maturity have a non-significant effect on self-efficacy and outcome expectancy. Therefore, this research suggests that the government should consider developing assistance and subsidy policies to promote enterprise investment in smart manufacturing, and to collaborate with firms to further develop market demand for Industry 4.0 products and services. Combining enhanced enterprise self-efficacy and increased expected return on investment will enhance enterprise intention to invest in Industry 4.0. This research provides concrete advice on the development of smart manufacturing, along with an outline of Industry 4.0 for government, academics and provides another sustainable development thinking for the operation.

This study is subject to several limitations that could potentially be resolved by future research. First, our study relies on a survey of manufacturing and hightech enterprises in Taiwan, thus its findings may not precisely reflect the perceptions of similar industries in other countries due to cultural differences. Second, there may be other predictors beyond perceived demand market maturity, perceived supply market maturity, government subsidy policies, self-efficacy, and outcome expectancy. Other industry specific considerations and adoptive variables can be introduced in future research to improve coverage and reliability. Third, research data was collected using an online questionnaire which may have introduced a self-selection bias. We propose that future research should rely on interview assisted quantitative methods.

Appendix A

Perceived demand market maturity					
1. My company perceives the smart manufacturing market as strong	1	2	3	4	5
2. My company sees sufficient demand for smart manufacturing in the future	1	2	3	4	5
3. Many enterprises in our industry need smart manufacturing	1	2	3	4	5
Perceived supply market maturity					
4. Smart manufacturing technology/equipment suppliers are easy to find	1	2	3	4	5
5. Sources of smart manufacturing technology/equipment suppliers are sufficient to demand	1	2	3	4	5
6. Needed smart manufacturing technology/equipment is easy to find	1	2	3	4	5
Government subsidy policies					
7. Government assistance policies fit our industry needs	1	2	3	4	5
8. Government subsidy policies fit our industry needs	1	2	3	4	5
9. Government R&D policies fit our industry needs	1	2	3	4	5
Self-efficacy					
10. My company is capable of importing sensor technology	1	2	3	4	5
11. My company is proficient in communication networks and device integration technologies	1	2	3	4	5
12. My company can import big data analysis technology	1	2	3	4	5
13. My company can import automatic control technology	1	2	3	4	5
14. My company can upgrade to smart manufacturing applications	1	2	3	4	5
Outcome expectancy					
15. My company has a large expected output value for smart manufacturing	1	2	3	4	5
16. My company has large expected custom manufacturing business opportunities	1	2	3	4	5
17. My company expects cost performance will be improved by upgrading to smart manufacturing	1	2	3	4	5
Enterprise investment intention in smart manufacturing					
18. My company is willing to enter the smart manufacturing industry	1	2	3	4	5
19. My company is willing to invest in the smart manufacturing industry	1	2	3	4	5
20. My company is willing to upgrade to smart manufacturing	1	2	3	4	5

References

1. Uckelmann, D.; Isenberg, M.-A.; Teucke, M.; Halfar, H.; Scholz-Reiter, B. Autonomous control and the internet of things: Increasing robustness, scalability and agility in logistic networks. In Unique radio innovation for the 21st century, Springer: 2011; pp. 163-181.
2. Kumar, S.; Suhaib, M.; Asjad, M.J.M.; Review, P.E. Industry 4.0: Complex, disruptive, but inevitable. Management and Production Engineering Review 2020, 11.
3. Li, L.J.T.F.; Change, S. China's manufacturing locus in 2025: With a comparison of “Made-in-China 2025” and “Industry 4.0”. Technological Forecasting and Social Change 2018, 135, 66-74.
4. Jain, N.; Hudait, M.K.J.E.H.; Systems. III–V multijunction solar cell integration with silicon: Present status, challenges and future outlook. Energy Harvesting and Systems 2014, 1, 121-145.
5. Ejsmont, K.; Gladysz, B.; Kluczek, A.J.S. Impact of Industry 4.0 on Sustainability—Bibliometric Literature Review. Sustainability 2020, 12, 5650.
6. Kluczek, A.; Gladysz, B. Energy LCA-Oriented Sustainability Analysis Assessment Approach for Visualization of Energy-Efficient Manufacturing. In Proceedings of International Conference on Innovations Induced by Research in Technical Systems; pp. 61-72.
7. Kagermann, H.; Wahlster, W.; Helbig, J.J.F.B., Germany. Recommendations for implementing the strategic initiative Industrie 4.0: Final report of the Industrie 4.0 Working Group. Forschungsunion: Berlin, Germany 2013.
8. Ghobakhloo, M.J.I.J.o.P.R. Determinants of information and digital technology implementation for smart manufacturing. International Journal of Production Research 2020, 58, 2384-2405.
9. Radziwon, A.; Bilberg, A.; Bogers, M.; Madsen, E.S.J.P.e. The smart factory: exploring adaptive and flexible manufacturing solutions. Procedia engineering 2014, 69, 1184-1190.
10. Kang, H.S.; Lee, J.Y.; Choi, S.; Kim, H.; Park, J.H.; Son, J.Y.; Kim, B.H.; Do Noh, S.J.I.j.o.p.e.; technology, m.-g. Smart manufacturing: Past research, present findings, and future directions. International journal of precision engineering and manufacturing-green technology 2016, 3, 111-128.
11. Chen, T.; Tsai, H.-R.J.R.; manufacturing, c.-i. Ubiquitous manufacturing: Current practices, challenges, and opportunities. Robotics and computer-integrated manufacturing 2017, 45, 126-132.
12. Niesen, T.; Houy, C.; Fettke, P.; Loos, P. Towards an integrative big data analysis framework for data-driven risk management in industry 4.0. In Proceedings of 2016 49th Hawaii international conference on system sciences (HICSS); pp. 5065-5074.
13. Stock, T.; Seliger, G.J.P.C. Opportunities of sustainable manufacturing in industry 4.0. Procedia Cirp 2016, 40, 536-541.
14. Foidl, H.; Felderer, M. Research challenges of industry 4.0 for quality management. In Proceedings of International conference on enterprise resource planning systems; pp. 121-137.
15. Bandura, A.J.P.r. Self-efficacy: toward a unifying theory of behavioral change. Psychol. Rev. 1977, 84, 191.
16. Bandura, A.; Cervone, D.J.O.b.; processes, h.d. Differential engagement of self-reactive influences in cognitive motivation. Organ. Behav. Hum. Decis. Process. 1986,

38, 92-113.
17. Compeau, D.R.; Higgins, C.A.J.M.q. Computer self-efficacy: Development of a measure and initial test. MIS quarterly 1995, 189-211.
18. Compeau, D.; Higgins, C.A.; Huff, S.J.M.q. Social cognitive theory and individual reactions to computing technology: A longitudinal study. MIS quarterly 1999, 145-158.
19. Huang, H.-M.; Liaw, S.-S.J.C.i.h.b. Exploring users' attitudes and intentions toward the web as a survey tool. Comput. Human Behav. 2005, 21, 729-743.
20. Lee, E.W.; Ho, S.S.; Lwin, M.O.J.C.i.H.B. Extending the social cognitive model—Examining the external and personal antecedents of social network sites use among Singaporean adolescents. Comput. Human Behav. 2017, 67, 240-251.
21. Wang, R.-T.; Lin, C.-P.J.J.o.E.; Management, T. Understanding innovation performance and its antecedents: A socio-cognitive model. Journal of Engineering and Technology Management 2012, 29, 210-225.
22. Yilmaz, R.J.C.i.H.B. Knowledge sharing behaviors in e-learning community: Exploring the role of academic self-efficacy and sense of community. Comput. Human Behav. 2016, 63, 373-382.
23. Ifinedo, P.J.C.i.H.B. Examining students' intention to continue using blogs for learning: Perspectives from technology acceptance, motivational, and social-cognitive frameworks. Comput. Human Behav. 2017, 72, 189-199.
24. Kwahk, K.-Y.; Park, D.-H.J.C.i.H.B. The effects of network sharing on knowledge-sharing activities and job performance in enterprise social media environments. Comput. Human Behav. 2016, 55, 826-839.
25. Chen, S.-S.; Chuang, Y.-W.; Chen, P.-Y.J.K.-B.S. Behavioral intention formation in knowledge sharing: Examining the roles of KMS quality, KMS self-efficacy, and organizational climate. Knowledge-Based Systems 2012, 31, 106-118.
26. Easley, R.F.; Devaraj, S.; Crant, J.M.J.J.o.M.I.S. Relating collaborative technology use to teamwork quality and performance: An empirical analysis. Journal of Management Information Systems 2003, 19, 247-265.
27. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D.J.M.q. User acceptance of information technology: Toward a unified view. MIS quarterly 2003, 425-478.
28. Khang, H.; Han, E.-K.; Ki, E.-J.J.C.i.H.B. Exploring influential social cognitive determinants of social media use. Comput. Human Behav. 2014, 36, 48-55.
29. Hatlevik, O.E.; Guðmundsdóttir, G.B.; Loi, M.J.C.; Education. Digital diversity among upper secondary students: A multilevel analysis of the relationship between cultural capital, self-efficacy, strategic use of information and digital competence. Computers & Education 2015, 81, 345-353.
30. Krumsvik, R.J.J.H.u. Digital competence in the Norwegian teacher education and schools. Högre utbildning 2011, 1, 39-51.
31. McAlister, A.L.; Perry, C.L.; Parcel, G.S.J.H.B. How individuals, environments, and health behaviors interact. Health Behavio 2008, 169.
32. Dickson, J.W.J.A.o.M.J. The adoption of innovative proposals as risky choice: A model and some results. Acad. Manage. J. 1976, 19, 291-303.
33. Mir, M.; Casadesús, M.; Petnji, L.H.J.J.E.T.M. The impact of standardized innovation management systems on innovation capability and business performance: An empirical study. Journal of Engineering and Technology Management 2016, 41, 26-44.
34. Ratten, V.; Ratten, H.J.E.j.o.i.m. Social cognitive theory in technological innovations. European journal of innovation management 2007.
35. Cingöz, A.; Akdoğan, A.A.J.P.-S.; Sciences, B. An empirical examination of

performance and image outcome expectation as determinants of innovative behavior in the workplace. Procedia-Social and Behavioral Sciences 2011, 24, 847-853.
36. Moghavvemi, S.; Sharabati, M.; Paramanathan, T.; Rahin, N.M.J.T.I.J.o.M.E. The impact of perceived enjoyment, perceived reciprocal benefits and knowledge power on students' knowledge sharing through Facebook. The International Journal of Management Education 2017, 15, 1-12.
37. Niederhauser, D.S.; Perkmen, S.J.C.i.H.B. Beyond self-efficacy: Measuring pre-service teachers' instructional technology outcome expectations. Comput. Human Behav. 2010, 26, 436-442.
38. Aydin, R.; Kwong, C.K.; Ji, P.; Law, H.J.N. Market demand estimation for new product development by using fuzzy modeling and discrete choice analysis. Neurocomputing 2014, 142, 136-146.
39. Triebswetter, U.; Wackerbauer, J.J.J.o.C.P. Integrated environmental product innovation in the region of Munich and its impact on company competitiveness. Journal of Cleaner Production 2008, 16, 1484-1493.
40. Slater, S.F.; Narver, J.C.J.S.m.j. Customer-led and market-oriented: let's not confuse the two. Strategic management journal 1998, 19, 1001-1006.
41. Campos, E.B.; de Pablos, P.O.J.I.J.o.T.M. Innovation and learning in the knowledge-based economy: challenges for the firm. International Journal of Technology Management 2004, 27, 531-532.
42. Alegre, J.; Chiva, R.J.T. Assessing the impact of organizational learning capability on product innovation performance: An empirical test. Technovation 2008, 28, 315-326.
43. Lin, R.-J.; Tan, K.-H.; Geng, Y.J.J.o.C.P. Market demand, green product innovation, and firm performance: evidence from Vietnam motorcycle industry. Journal of Cleaner Production 2013, 40, 101-107.
44. Mu, J.; Peng, G.; MacLachlan, D.L.J.T. Effect of risk management strategy on NPD performance. Technovation 2009, 29, 170-180.
45. Meehan, J.; Bryde, D.J.B.s.; environment, t. Sustainable procurement practice. Business strategy and the environment 2011, 20, 94-106.
46. Seuring, S.; Müller, M.J.J.o.c.p. From a literature review to a conceptual framework for sustainable supply chain management. Journal of cleaner production 2008, 16, 1699-1710.
47. Rolfstam, M.J.I.T.E.J.o.S.S.R. An institutional approach to research on public procurement of innovation. Journal of Social Science Research 2012, 25, 303-321.
48. Phillips, W.; Johnsen, T.; Caldwell, N.; Chaudhuri, J.B.J.T.A.; Management, S. The difficulties of supplying new technologies into highly regulated markets: the case of tissue engineering. Technology Analysis & Strategic Management 2011, 23, 213-226.
49. Mahapatra, S.K.; Das, A.; Narasimhan, R.J.J.o.O.M. A contingent theory of supplier management initiatives: effects of competitive intensity and product life cycle. Journal of Operations Management 2012, 30, 406-422.
50. Porter, M.E. Competitive advantage of nations: creating and sustaining superior performance; simon and schuster: 2011.
51. Watkins, A.; Papaioannou, T.; Mugwagwa, J.; Kale, D.J.R.P. National innovation systems and the intermediary role of industry associations in building institutional capacities for innovation in developing countries: A critical review of the literature. Research Policy 2015, 44, 1407-1418.
52. Hsu, F.-M.; Horng, D.-J.; Hsueh, C.-C.J.T. The effect of government-sponsored R&D programmes on additionality in recipient firms in Taiwan. Technovation 2009, 29, 204-

217.
53. Perez-Sebastian, F.J.E.l. Market failure, government inefficiency, and optimal R&D policy. Economics letters 2015, 128, 43-47.
54. Beugelsdijk, S.; Cornet, M.J.J.o.m.; governance. 'A far friend is worth more than a good neighbour': Proximity and innovation in a small country. Journal of management and governance 2002, 6, 169-188.
55. Romijn, H.; Albaladejo, M.J.R.p. Determinants of innovation capability in small electronics and software firms in southeast England. Research policy 2002, 31, 1053-1067.
56. Souitaris, V.J.R.p. Technological trajectories as moderators of firm-level determinants of innovation. Research policy 2002, 31, 877-898.
57. Doh, S.; Kim, B.J.R.P. Government support for SME innovations in the regional industries: The case of government financial support program in South Korea. Research Policy 2014, 43, 1557-1569.
58. Hussinger, K.J.J.o.a.e. R&D and subsidies at the firm level: An application of parametric and semiparametric two-step selection models. Journal of applied econometrics 2008, 23, 729-747.
59. Reischauer, G.J.T.F.; Change, S. Industry 4.0 as policy-driven discourse to institutionalize innovation systems in manufacturing. Technological Forecasting and Social Change 2018, 132, 26-33.
60. Pellas, N.J.C.i.H.B. The influence of computer self-efficacy, metacognitive self-regulation and self-esteem on student engagement in online learning programs: Evidence from the virtual world of Second Life. Comput. Human Behav. 2014, 35, 157-170.
61. Pihlajamaa, M.J.J.o.E.; Management, T. Going the extra mile: Managing individual motivation in radical innovation development. Journal of Engineering and Technology Management 2017, 43, 48-66.
62. Pajares, F.J.S.-e.b.o.a. Self-efficacy during childhood and adolescence. Self-efficacy beliefs of adolescents 2006, 5, 339-367.
63. Schunk, D.H. Social cognitive theory and self-regulated learning. In Self-regulated learning and academic achievement, Springer: 1989; pp. 83-110.
64. Yeagley, E.E.; Subich, L.M.; Tokar, D.M. Modeling college women's perceptions of elite leadership positions with Social Cognitive Career Theory. J Vocat Behav 2010, 77, 30-38, doi:10.1016/j.jvb.2010.02.003.
65. Zikic, J.; Saks, A.M.J.J.o.V.B. Job search and social cognitive theory: The role of career-relevant activities. J Vocat Behav 2009, 74, 117-127.
66. Blanco, Á.J.J.o.V.B. Applying social cognitive career theory to predict interests and choice goals in statistics among Spanish psychology students. J Vocat Behav 2011, 78, 49-58.
67. Yuan, F.; Woodman, R.W.J.A.o.m.j. Innovative behavior in the workplace: The role of performance and image outcome expectations. Acad. Manage. J. 2010, 53, 323-342.
68. Bhattacherjee, A.J.M.q. Understanding information systems continuance: An expectation-confirmation model. MIS quarterly 2001, 351-370.
69. Tan, M.; Teo, T.S.J.J.o.t.A.f.i.S. Factors influencing the adoption of Internet banking. Journal of the Association for information Systems 2000, 1, 5.
70. Lu, H.P.; Hsiao, K.L.J.I.r. Understanding intention to continuously share information on weblogs. Internet research 2007.
71. Ratten, V.J.A.M.J. Cloud computing: A social cognitive perspective of ethics,

entrepreneurship, technology marketing, computer self-efficacy and outcome expectancy on behavioural intentions. Australasian Marketing Journal (AMJ) 2013, 21, 137-146.
72. Chin, W.W.; Marcolin, B.L.; Newsted, P.R.J.I.s.r. A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. Information systems research 2003, 14, 189-217.
73. HAIR JUNIOR, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E.; Tatham, R.L.J.N.J. Multivariate data analysis. 1998.
74. Fornell, C.; Larcker, D.F.J.J.o.m.r. Evaluating structural equation models with unobservable variables and measurement error. Journal of marketing research 1981, 18, 39-50.
75. Bagozzi, R.P.; Yi, Y.J.J.o.t.a.o.m.s. On the evaluation of structural equation models. Journal of the academy of marketing science 1988, 16, 74-94.
76. Liu, S.; Kasturiratne, D.; Moizer, J.J.I.M.M. A hub-and-spoke model for multi-dimensional integration of green marketing and sustainable supply chain management. Industrial Marketing Management 2012, 41, 581-588.
77. Hsu, C.-W.; Hu, A.H.J.J.o.c.p. Applying hazardous substance management to supplier selection using analytic network process. Journal of cleaner production 2009, 17, 255-264.
78. Chiou, T.-Y.; Chan, H.K.; Lettice, F.; Chung, S.H.J.T.R.P.E.L.; Review, T. The influence of greening the suppliers and green innovation on environmental performance and competitive advantage in Taiwan. Transportation Research Part E: Logistics and Transportation Review 2011, 47, 822-836.
79. Görg, H.; Strobl, E.J.E. The effect of R&D subsidies on private R&D. Economica 2007, 74, 215-234.
80. Hong, J.; Feng, B.; Wu, Y.; Wang, L.J.T. Do government grants promote innovation efficiency in China's high-tech industries? Technovation 2016, 57, 4-13.
81. Celik, V.; Yesilyurt, E.J.C.; Education. Attitudes to technology, perceived computer self-efficacy and computer anxiety as predictors of computer supported education. Computers & Education 2013, 60, 148-158.
82. Lord, R.G.; Gatti, P.; Chui, S.L.J.O.B.; Processes, H.D. Social-cognitive, relational, and identity-based approaches to leadership. Organ. Behav. Hum. Decis. Process. 2016, 136, 119-134.
83. Li, D., Liu, S., Wang, B., Yu, C., Zheng, P., Li, W. Trustworthy AI for human-centric smart manufacturing: A survey. Journal of Manufacturing Systems, 2025, 78, 308-327.