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# What Drives Industry 4.0 Technologies Adoption? Evidence from a SEM-Neural Network Approach in the Context of Vietnamese Firms

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**Abstract:** The development of the Industrial Revolution 4.0 has far-reaching effects on all aspects of life, the economy, and society, bringing various growth opportunities for businesses. However, businesses are still hesitant to apply these new technologies. On a research sample from a survey of 396 Vietnamese enterprises, the study uses the SEM-neural network method to determine the relationship and importance of five groups of factors affecting the firms' Industry 4.0 technologies adoption. The results suggest that five groups of factors, including Perceived characteristics, Technological competencies, CEO characteristics, Environmental characteristics, and Subjective Norms, all positively and significantly impact the Industry 4.0 technologies adoption in Vietnam. In particular, Technological competencies are the most influential factors according to the SEM method, while Subjective norms factors have the most decisive impact according to the neural-network method. Moreover, the research also found that adopting Industry 4.0 technologies depends on different company characteristics, such as age, size, status, and industry.

**Keywords:** Industry 4.0 technology; innovation implementation; technology diffusion; Vietnamese firms; SEM-neural network

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## 1. Introduction

The Fourth Industrial Revolution has far-reaching impacts on all aspects of life (economy, society, security, and environment), on all objects (government, enterprises/business, organizations, and individuals), in all areas, and at all levels (global, regional, and within each country). This revolution fundamentally changes how people create products, thereby creating a "revolution" in the organization of production-value chains. It is restructuring almost all industries on a global scale. These changes herald the transformation of human society's production, management, and governance system. These impacts are positive in the long term but also create short- and medium-term challenges, which are reported in the current literature [1–3]. Therefore, improvising with the Fourth Industrial Revolution requires comprehensive and synchronous coordination involving all organizations, individuals, and governments in the world from the public and private sectors as a whole [4].

However, according to survey reports from Deloitte Insights [5] or the research of Geissbauer et al. [6], despite the fast development and the opportunities that 4.0 technology brings, businesses are still hesitant to apply these new technologies, represented by low readiness levels. Therefore, the question of what factors could drive Industry 4.0 technologies adoption by enterprises is receiving increasing attention from researchers and policymakers.

By using survey data from Vietnamese enterprises, this research aims to investigate the main factors driving enterprises' adoption of Industry 4.0 technologies. While most previous studies use the context of developed countries or technology leaders, such as the US, China, or Europe, the case of Vietnam is quite specific. Vietnam is a developing economy in Southeast Asia, with more than 90% of enterprises being small and medium, contributing to more than 40% of the country's GDP [7,8]. According to the Ministry of Industry and Trade of Vietnam (2022), many of these enterprises are small business households, so they do not have a reputation and brand name, the management level is still weak, and there is no stable business model. Therefore, they are not interested in digital transformation and are not keeping up with the concepts of Revolution 4.0.

While the Fourth Industrial Revolution has been penetrating all aspects of the global economy and society, it has opened up opportunities and posed many challenges for the socioeconomic development of Vietnam in general and Vietnamese enterprises in particular. In order to match the global trend, the Vietnamese government has issued many relevant resolutions and directives (for example, Directive 16/CT-TTg, dated 4 May 2017, of the Prime Minister on strengthening the access to the Fourth Industrial Revolution; Directive No. 02/CT-TTg, dated 26 April 2022, of the Prime Minister on developing e-Government towards the digital government and promoting national digitalization). At the same time, they are also actively developing a national digital transformation plan and preparing a development strategy for the 4.0 revolution, which emphasizes the role of Industry 4.0 technologies adoption in Vietnamese enterprises [9]. In that context, identifying factors driving Industry 4.0 technologies adoption in Vietnam can make significant contributions and policy implications.

While previous studies have mainly focused on exploiting data sets belonging to small and medium companies, belonging to a specific industry, and/or related to one specific technology [10–14], this study contributes to the theoretical basis by studying the factors affecting the adoption of Industry 4.0 technologies in general based on analyzing the survey data set of enterprises in Vietnam, diverse in size, age, industry, and status. This approach could enhance the generalizability of the results obtained. In addition, the study is also one of the first to provide empirical evidence for the specific context of a developing Southeast Asian country, such as Vietnam. Moreover, through a review of previous studies, there are rarely studies on the same topic using the SEM-neural network method. Hence, this paper is pioneering research for the Vietnamese context using this methodology. In addition, based on inheriting existing models and theories, the study combines theories and proposes a new framework for Industry 4.0 technologies diffusion, including five groups of factors: perceived technological characteristics, technological competencies, CEO characteristics, environmental characteristics, and subjective norms. We also try to verify whether firms' Industry 4.0 technologies adoption diverges depending on different sizes, ages, statuses, and industries. Finally, we also try to propose relevant policy and management implications based on research results.

The study has a five-part structure. The following section presents a brief overview of previous studies related to the topic before describing the research method in Section 3. We are drawn to discussions in Section 5 after analyzing research results in Section 4.

## 2. Literature Review

### *2.1. Industry 4.0 Technologies*

The Industrial Revolution refers to the breakthrough and radical development ladders in the process of industrial development, profoundly changing the economic systems and social structures. Until now, the world has experienced four Industrial Revolutions. The first revolution took place at the beginning of the 18th century with the achievements of mechanization and the steam engine introduction. The second Industrial Revolution appeared between the late 19th and early 20th centuries with the invention of the electric motor and the assembly line to create large-scale production. The third industrial revolution started in the 1970s, characterized by using electronic equipment and information technology, such as the internet, to automate production. From the beginning of the 21st century, the world entered the fourth industrial revolution, also known as the Industrial Revolution 4.0 [12,15–17]. The Fourth Industrial Revolution, formed in the middle of the second decade of the 21st century, has profoundly changed the entire social life and the global economy. The concept of Industry 4.0 first appeared in 2011 by the German Industry–Science Research Alliance [18]. The term "Industry 4.0" is often understood as efficient automated production processes supported by the ability to connect and communicate between machines through digital connectivity across the value chain [4,19].

According to Kovács and Husti [20], the 4.0 Industrial revolution is considered an extension of the third industrial revolution, in which information and communication technology is used much more widely than before in all fields of human life. In this new revolution, interconnectedness matters. Not only are electronic computers connected to networks, but almost all areas of human activity, production lines, scientific research, education, health care, services, entertainment, and so on, are all linked into "smart networks", which opens the era of the Internet of Things [16,21,22]. Thanks to this connectivity, AI-equipped products, machines, and processes will be able to quickly adapt to changing environmental factors [23], leading companies to become more agile and more responsive to opportunities and challenges from the business environment [24]. The term "Industry 4.0" (I4.0) also includes the increasing digitalization of the entire supply chain, which connects disparate objects and systems through the real-time exchange of data [21].

According to Posada et al. [25] and Roblek et al. [26], there are five key elements of Industry 4.0, including (i) digitization, optimization, and customization of production; (ii) automation and adaptation; (iii) human and machine interaction; (iv) value-added services and stores, and (v) automatic data exchange and communication. Meanwhile, Zezulka et al. [27] suggested that the term Industry 4.0 involves three factors: (i) digitization and integration of networks, (ii) digitization of products and services, and (iii) new market models. Moreover, according to the Boston Consulting Group [28], Industry 4.0 includes nine pillars, including Big Data and Analytics; Autonomous Robots; Simulation; Horizontal and Vertical Systems; Intergration; The Industrial Internet of Things; Cybersecurity; The Cloud; Additive Manufacturing; and Augmented Reality (the definition and concept of each pillar are presented in Appendix A).

In general, the fourth industrial revolution is entirely different from the three other industrial revolutions. The speed of Industry 4.0 is without precedent in history. If the previous industrial revolutions took place at a linear rate, the growth rate of the fourth industrial revolution is exponential.

With the opportunities that 4.0 technology brings, more and more businesses have plans and actions to implement these new technologies. In Germany, according to a survey by Staufen [29], the number of German companies considering adopting Industry 4.0 technologies increased from 66% to 91% within just four years, from 2014 to 2018. In the Czech Republic, the number of companies that engage in Industry 4.0 technologies in one year reaches 40%, and 20% of total companies are in the transition phase [30]. However, these figures only reflect the situation in Germany and the Czech Republic, which are rated as the leaders of Industry 4.0 [31]. At the international level, a study of 1155 businesses in 26 countries by Geissbauer et al. [6] shows that only 31% of businesses have started to apply Industry 4.0 technologies. Deloitte Insights [5] reported survey results, polling 1600 C-level executives across 19 countries to investigate whether companies are ready to deploy Industry 4.0 technologies. While most CEOs conceptually understand the changes and opportunities that Industry 4.0 could bring, they are uncertain about how they can act to benefit from those changes. These CEOs acknowledge that they are not ready to exploit the changes related to Industry 4.0. As a result, this lack of readiness has made them reluctant to change their current strategies, and they tend to continue focusing on traditional business practices instead.

Therefore, our research paper aims to contribute to the literature on Industry 4.0 by clarifying the factors affecting the adoption of Industry 4.0 technologies in enterprises in developing regions, which could provide additional references for managers and policy-makers in the same field.

### *2.2. Conceptual Background*

Many authors have developed various models and theories to explain the application of technological innovation in enterprises. Some theoretical models focus on studying the characteristics of the technology itself that affect a firm's adoption decisions. Others switch their attention toward external business environment factors, such as the characteristics of the industry [32]. However, studies on adopting new technologies, especially those of Industry 4.0, are primarily carried out in developed countries or countries with solid innovation histories [33,34]. By scanning the related literature review, the number of studies on this topic for the developing country segment is limited.

Overall, researchers mostly use three dominant models as their background theories of technology management, including (i) The Diffusion of Innovation (DOI) by Rogers et al. [35]; (ii) the Technology, Organization, and Environment (TOE) framework, developed by Tornatzky et al. [36]; and (iii) the Theory of Planned Behavior (TPB), suggested by Ajzen [37].

The Diffusion of Innovation theory (DOI), suggested by Rogers et al. [35], is one of the most comprehensive and fundamental theories. It describes the adoption process and clearly shows how and why it is applied. In particular, the attributes of a new technology, which, according to DOI, play an essential role in persuading firms to adopt it, are often mentioned in the theoretical background of many different studies on related topics [38,39].

While the DOI theory focuses mainly on the attributes of the technology itself when considering adoption, the TOE framework of Tornatzky et al. [36] is more concerned with organizational and environmental factors. The TOE framework describes the influence of the company context on the decision and implementation of technological innovation (Baker, 2012), highly appreciated by many authors and considered a basic theory when conducting firm-level studies in different contexts [40]. Many authors have combined the theory of DOI and TOE to give more comprehensive and better results on the determinants of technological innovation application [40–42].

The third most popular approach uses social and individual decision making theories to describe and explain firms' decisions to adopt innovative technologies. Three widely used models in this approach include the Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA), and the Theory of Planned Behavior (TPB) [43]. In particular, the theory of planned behavior (TPB) developed by Ajzen (1991) is an extension of the theory of rational action (TRA) [44]. These theories hypothesize that an individual's intention to perform a behavior is a determining factor in performing that behavior. Thus, the individual's attitude towards behavior and subjective norms determine the intention to perform. Attitude towards behavior refers to the extent to which a person has a positive or negative assessment of the behavior. Subjective norm refers to perceived social pressure to perform or not to perform a behavior [45].

Overall, all the models mentioned above agree that technological attributes are essential to innovation implementation. In addition, the TOE model further considers the impact of the surrounding environment (industry, competitors, and government support) and organizational factors on the firm's adoption of new technology. Meanwhile, the TPB model has added the role of subjective norms in innovation implementation in a firm.

This study uses the combination of these three popular models to explore the factors affecting Industry 4.0 technologies adoption in Vietnamese companies.

### *2.3. Hypotheses Development and Model Development*

#### 2.3.1. Perceived Technology Characteristics

Many studies based on the classical theory of diffusion of innovation provide various concepts and empirical studies related to technology's evaluation, adoption, and implementation [46]. In particular, the research of Rogers et al. [35] is considered the most outstanding and easy to understand. By reviewing more than 3000 studies on the application of new technology in enterprises, Rogers et al. [35] proposed that different attributes of technology and how firms perceive these attributes significantly impact their decision to adopt. Five critical characteristics of the technology are often considered to affect technological adoption in enterprises, including relative advantage (how much better is the new technology compared to the previous one), compatibility (how well the technology works relevant to the business), complexity (the difficulty and complexity of the technology that businesses perceive when applying it), observability (how observable are the results from the technology implementation), and trialability (whether the technology can be tested before it is officially adopted). Among these attributes, the perceived relative advantage factor is mentioned extensively in the research on Industry 4.0 technologies adoption in businesses. Lin et al. [47] reported that perceived relative advantages positively impact the intention to apply Industry 4.0 technologies in firms. Many other authors also reported similar results [48–50]. Industry 4.0 technologies enable businesses to gain a competitive advantage, reduce costs, improve profitability, and efficiency [51], and open up new business opportunities with new products and services [52].

Supporting the results of Rogers et al. [35], many other studies also show a positive relationship between perceived compatibility and the intention to adopt innovative technology [49,53,54]. Compatibility refers to how well the new technology fits the values, norms, and needs of the business [55]. In addition, for a successful technology transformation, there needs to be an appropriate fit in the existing business model and strategy [49]. Moreover, the more likely the technology is to be tested before deployment, the easier it is for the enterprise to make adoption decisions [55–57].

Based on the existing literature review, we build below a hypothesis related to technological attributes as follows:

**H1.** *Perceived Technology characteristics are positively associated with Industry 4.0 technologies adoption.*

#### 2.3.2. Technological Competencies

As an organizational factor, Technological Competencies are mentioned in many studies on new technologies adoption. According to Cohen and Levinthal [58], whether a company decides to apply new technology depends on its absorptive capacity, which is understood as the capacity of the firm to assess, assimilate, exploit, and apply new knowledge to improve its business performance. In the context of research on Industry 4.0 technologies, absorptive capacity is associated with the technological competencies of enterprises.

First, firms usually develop their technological competencies through improvement, innovation, and R and D activities (internal or in combination with external), which play an essential role in promoting their absorptive ability and creating innovations [58,59]. The adoption or the experience of older technologies significantly impacts a firm's Technological Competencies through learning effects [60–63]. Therefore, the more R and D and innovation businesses have done, the more likely they will adopt Industry 4.0 technologies. Many studies support that a firm's history of R and D, and innovation and previous technological experiences make it easier to absorb new technology, thus positively impacting the adoption of new technology in enterprises [61,64–69].

Furthermore, human capital is also a critical part of the firm's absorptive capacity. The role of human capital in developing firms' absorptive ability and facilitating the early adoption of new technologies has been emphasized in many previous studies [58,70–72]. Indeed, one of the typical features of new Industry 4.0 technologies, such as machine learning, cloud computing, and big data, is complexity. Therefore, the effective implementation and exploitation of these technologies often require quite a lot of specific knowledge, expertise, qualifications, and skills [73]. The lack of experts with information technology and scientific backgrounds makes many businesses, particularly small- and medium-sized enterprises, nervous when entering the transition to Industry 4.0 [74]. A lack of scientific backgrounds among staff can hinder or prevent the adoption of new technology if owners believe that the technology can only be used by professionals. Training staff and hiring experienced professionals often entail significant costs [74,75]. Therefore, enterprises with employees with scientific backgrounds often have a comparative advantage and are willing to test and apply new technologies, such as Industry 4.0 technologies, due to their ability to absorb and exploit better. In other words, companies with human capital with a high level of scientific background are often the earliest adopters of new technologies [58]. In addition, Cragg and King [76] also reported that lack of knowledge about information technology is one of the biggest obstacles for enterprises to apply new technologies, such as Industry 4.0. Indeed, due to the complex nature and direct IT relevance of Industry 4.0 technologies, companies with employees equipped with IT skills will have an advantage when deploying innovations or handling unexpected situations related to new technology [77,78].

From the above analysis, we expect the firms' technological competencies or the absorptive capacity to have a positive impact on Industry 4.0 technologies adoption, as suggested by the below hypothesis:

**H2.** *Technological Competencies are positively associated with Industry 4.0 technologies adoption.*

#### 2.3.3. CEO Characteristics

The top manager's characteristics can significantly influence the decision to adopt new technologies in enterprises [79]. Indeed, the CEO is often the key figure in making corporate decisions, including innovation activities, so the CEO's characteristics also determine the overall management style of the business [35]. These characteristics include decentralized structure, visionary leadership, innovativeness, and IT knowledge.

First, the CEO's characteristics are well reflected in the leadership style and the firm's organizational structure. The impact of an enterprise's organizational structure (centralized or decentralized) on adopting and implementing new technologies has been largely studied in past literature [80,81]. Most authors argue that decentralized firms tend to deploy new technology more than centralized-structured ones. The reason is that the nature of the decentralized structure is to empower employees to make decisions and encourage them to participate in value creation for the business [82]. This structure is often accompanied by the requirement for faster and more extensive information processing, so the cost of promoting coordination among staff is considerable [83,84]. By establishing a real-time information assimilation and distribution network, Industry 4.0 technologies help improve information transparency, maximize information transmission and processing, and create favorable conditions for decision making at all enterprise levels. New technologies, such as AI and machine learning, suggest solutions, accordingly, supporting easier decision making.

According to Hansen and Kahnweiler [85], a CEO's ability to create and articulate a vision in a realistic, credible, engaging, and positive manner is positively related to corporate innovation. Visionary leaders are often more concerned with organizational learning [86], thus often advocating for creating and maintaining a learning environment that facilitates innovation [87]. New technologies play an essential role in this process by facilitating knowledge transfer between people, processing, and normalizing information, then transforming it into new knowledge [88]. Therefore, visionary leaders often advocate for new technology. Moreover, according to Zappalà and Gray [89], a more entrepreneurial, risk-taking, innovative, and creative business manager is considered a critical factor for technology adoption. Many other authors also agree that firms with CEOs or owners with IT knowledge and innovative spirit are more likely to adopt new technologies [39,41,75,90–92]. According to Thong [75], other enterprise members can only promote adopting new technology if the CEO intends to innovate. In addition, the CEO's IT knowledge can also increase the ability of enterprises to apply new technology [75]. If they are not familiar with the basic technologies, business owners or CEOs will be hesitant to adopt more complex technologies. Many executives who lack basic IT knowledge and awareness do not know the benefits of these technologies. Therefore, they often assume these are not necessarily beneficial for their business [93]. This fact implies that if these CEOs have more IT knowledge, they will likely adopt these new technologies sooner [75].

From the above arguments, we propose the following hypothesis:

**H3.** *CEO characteristics are positively associated with Industry 4.0 technologies adoption.*

#### 2.3.4. Environmental CHARACTERISTICS

According to the TOE model, the business environment has a significant impact on firms' strategic considerations, including decisions to adopt Industry 4.0 technologies. This environmental context may include industry, competitors, and government support [36]. Other studies that approach institutional theory emphasize the role of competitive pressures and trading partners [94,95]. This paper limits the environmental context to four factors: competitive pressure, market turbulence, government support, and technology spillover.

First, many previous studies have recognized the relationship between competitive pressure and innovation adoption [96,97]. In fact, the advent of Industry 4.0 not only brings many opportunities but also leads to particular challenges, significantly increasing competitive pressure in most industries [98]. New competitors are emerging quickly, equipped with new technologies, and provide more innovative solutions to customers, combined with differentiated business models, threatening the position of established businesses. According to Kiel et al. [99], the increasing competitive pressure and more accessible entrance for new competitors are the most challenging parts of the Industry 4.0 era. In order to survive in this competitive context, many businesses have applied new technologies with the expectation of creating more competitive advantages over their competitors, thanks to the technology's ability to increase speed, quality, and efficiency and create innovations and even new products [100–102]. Furthermore, the current competitive environment also requires a high level of information transparency, which leads to more risks of cyber attacks and more challenges in information security. In that context, many studies indicate that enterprises should innovate their current business models by applying new technologies systematically [98,99,103]. However, reviewing previous studies, the impact of competitive pressure on adopting new technologies has not yet reached a consistent conclusion. While Spanos and Voudouris [97] report that higher competitive pressure encourages firms to apply new technologies by creating opportunities to outperform competitors [42]. On the other hand, the study of Rodríguez-Ardura and Meseguer-Artola [104] concluded the negative relationship between these two subjects. However, Pan and Jang [105] argue that competitive pressure has no significant impact on adopting new technology in enterprises. In this study, we expect that competitive pressure can motivate Vietnamese enterprises to apply Industry 4.0 technologies.

Second, firms operating in turbulent markets are more likely to adopt new technologies due to the constant need to make additional adjustments to adapt to changes [106]. An environment is considered turbulent when there are rapid and continuous changes in customer preferences and needs or even technology. These markets are often unpredictable and uncertain [96,107]. According to Trainor et al. [108], market turbulence can change customer expectations and needs dramatically and rapidly. In order to deal with this phenomenon, businesses tend to process more information, be more proactive, and conduct more adjustments and adaptations. Therefore, the company will devote more attention to analysis and innovation to ensure its competitive advantages, so it will be more likely to adopt new technology [109].

Third, many related studies emphasize the role of government in disseminating and deploying new technology in enterprises [110]. The reason is that the government can set related regulations to facilitate the exploitation and deployment of new technologies, thus benefiting the business [110–112]. For example, the government can introduce tax reduction measures, supporting businesses to overcome financial barriers when transitioning to Industry 4.0. Moreover, the government also plays a vital role in the dissemination and communication of technology [113]. In addition to facilitating financial and communication-related facilitation, governments can create a more appropriate environment for businesses wishing to adopt Industry 4.0 technologies. For example, they can set legal boundaries, encourage the construction of more broadband, and promote education to deal with the industrial revolution 4.0 [114,115].

Finally, according to the epidemic model of Mansfield [116] and Bass [117], information transmission is a driving force of technology diffusion [66]. Accordingly, knowledge and information will be transmitted between businesses. As the number of businesses adopting new technologies increases over time, those remaining in contact with the pioneers will receive information about the new technology, then consider adopting it. Thus, whether a firm adopts a new technology is positively affected by the industry's degree of adoption or the technology spillover [61,118]. When a significant supplier or customer adopts a new technology, the business owner is likelier to adopt it [119]. According to Julien and Raymond [120] and J. Y. Thong and Yap [121], a firm will be interested in adopting new technology when competitors, trading partners, or even the entire industry is adopting it. Research by Parker [122] and Poon and Swatman [123] shows that small businesses are often forced to use new technologies by large companies. However, Hollenstein [61] and Khalifa [66] also notice that this effect also depends on the studied technology.

From the results of previous research related to the impact of the environmental context on new technologies adoption in business, we propose the following hypothesis:

**H4.** *Environmental characteristics are positively associated with Industry 4.0 technologies adoption.*

#### 2.3.5. Subjective Norms

According to Ajzen [37], subjective norms are the social influences or pressures that firms perceive to perform or not to perform certain behaviors. In other words, subjective norms indicate a firm's beliefs about how they are perceived by important external people when performing a particular behavior. Do the people important to them think they should engage in this behavior?

The subjective norm factor is well mentioned in the TPB model Ajzen [37] and TAM model [124], which are particularly well-established models for the prediction and explanation of behaviors in many different domains [125–127]. The authors suggest that an individual's social background can change the individual's perception of performing a behavior. Indeed, most people will take action when important people around them think they should, even if they do not want to or do not like it. This act demonstrates the human nature to view the thoughts of significant others as factual evidence for acceptance of the behavior.

A relationship between the subjective norms factor and the firm's acceptance of technology or innovation has been found in many related studies [43,45,128–130]. However, there are still other studies that conclude that subjective norms do not significantly affect the adoption of new technology [131,132].

From previous research studies, we expect that subjective norms have a positive impact on the application of Industry 4.0 technologies as the following hypothesis is stated:

**H5.** *Subjective norms are positively associated with Industry 4.0 technologies adoption.*

#### 2.3.6. Conceptual Framework of Industry 4.0 Technologies Adoption

The model in this study also controls some company and environment characteristics, such as the firm's size, the firm's age, corporate status, and industry, to better clarify the adoption of Industry 4.0 technologies.

Figure 1 illustrates the conceptual framework of Industry 4.0 technologies adoption in this research.

### *2.4. SEM-Neural Network Method*

Through a review of previous studies on the implementation of Industry 4.0 technologies in enterprises, there are diversified quantitative methods on different numbers of observations in different countries, as illustrated in Appendix B. However, our paper is the first to use the Sem-neural network method to investigate different factors driving Industry 4.0 technologies adoption in a developing country, such as Vietnam.

According to Haykin [133], the neural network is a "'massively parallel distributed processor made up of simple processing units, which have a natural propensity for storing experimental knowledge and making it available for use", which works similarly to the human brain. First, the neural network collects new knowledge from the external environment through the learning process, then stores them by the synaptic weights. Then, depending on the desired design goals and sample data, algorithms are applied to systematically adjust the synaptic weights to achieve the final goals [133].

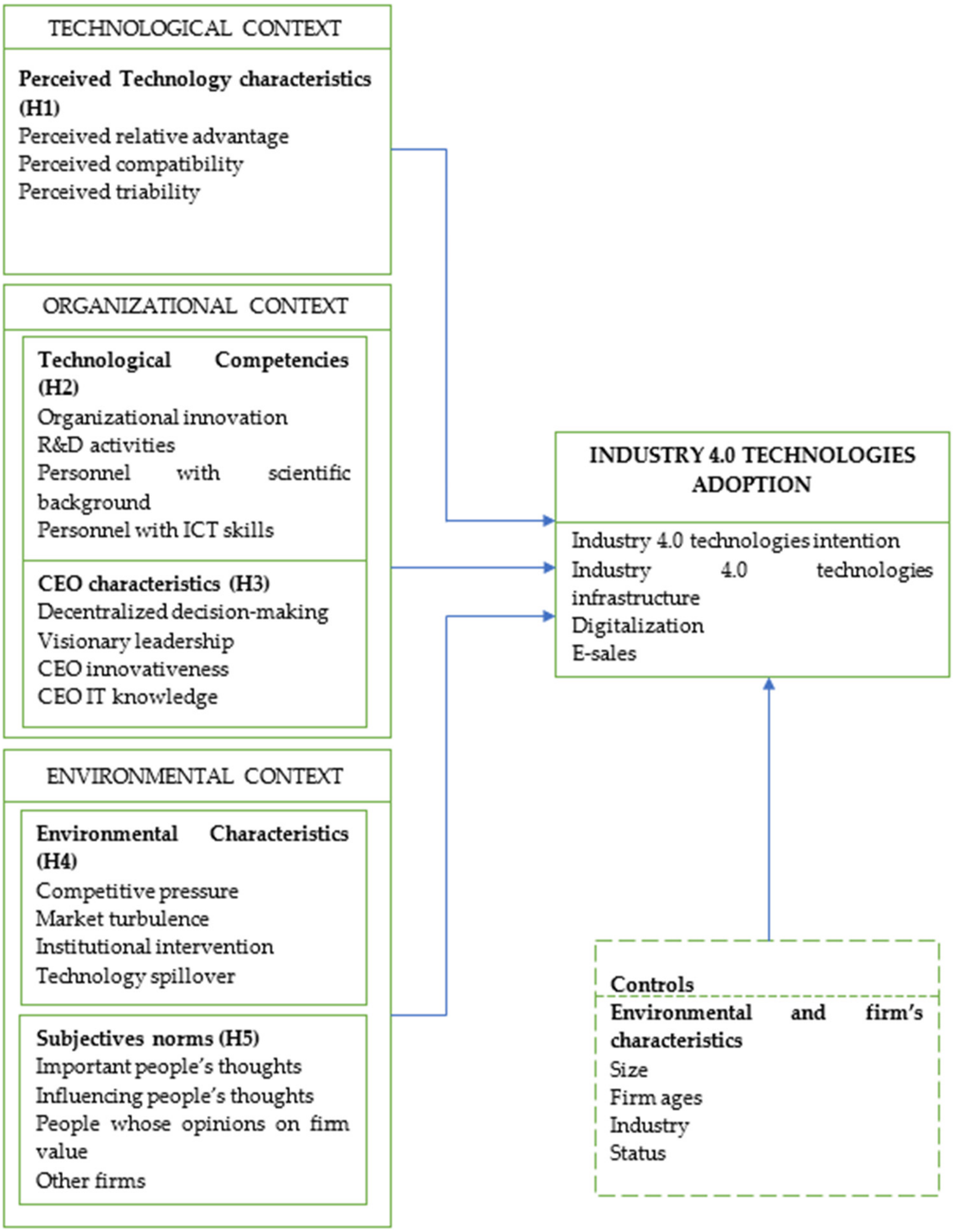


**Figure 1.** The conceptual framework of Industry 4.0 technologies adoption. Source: Authors' compilation.

Compared with traditional methods, such as logistic, multiple, and discriminant regression methods, neural networks have more advantages, accuracy, and efficiency [134–136]. First, the neural network model allows us to examine more complex linear and nonlinear relationships with more precise results. Second, the model's mapping of inputs and outputs does not need any assumption of specific distribution for variables [135]. The ability of neural networks to adapt and adjust to structural changes during data processing is also an advantage [134]. However, the main limitation of neural networks is model redundancy.

Furthermore, with the “black-box” approach, the neural network seems unsuitable for testing hypotheses and examining causal relationships. Researchers sometimes find it challenging to understand how neural networks suggest results [135]. The neural network method has been used in economics studies [137] and research on customer behavior [134,138]. However, the application in the field of technology application is limited.

In terms of SEM, this method is often used to verify hypothetical relationships but is rarely combined with other artificial intelligence algorithms [139,140]. The downside of SEM is that it is sometimes oversimplified.

In order to solve the limitations and take advantage of both SEM and neural networks, in this study, these two methods are combined to determine the factors affecting the firm’s Industry 4.0 technologies adoption in Vietnam. The SEM method will first test the overall research model and hypotheses. Then, based on the test results of SEM, the essential variables will be input into the neural network.

## 3. Research Methodology

### *3.1. Research Methodology*

We mainly used Google Scholar and ScienceDirect to search for related papers during the literature review and model establishment process. For the primary research question, “What drives Industry 4.0 technologies adoption in Vietnamese firms?”, our essential keywords are “Industry 4.0 technologies”, “technology adoption”, and “Vietnamese firms”. Then, we expand our search by brainstorming related words for each keyword (see Appendix D). Additionally, the reference lists in previous related articles are strongly significant and supportive sources when exploring the current literature, handy for the hypotheses’ development parts.

By technically inheriting previous studies, we use the below methods as data analysis and processing tools: Descriptive statistics method, Reliability testing of scale, Exploratory Factor Analysis (EFA), and hypothesis testing using SEM and neural network methods.

We performed EFA for each variable. This testing step ensures that observed variables measuring the same latent variable must be loaded into the correct position. It also removes inappropriate measurement criteria, aiming to avoid potential multicollinear. In particular, this test evaluates the reliability of each scale by using the Cronbach alpha index, which requires an alpha greater than 0.6 and an item-to-total correlational index greater than 0.3.

The SEM model is an extension of the general linear model (GLM), allowing the researcher to test a set of regression equations simultaneously. SEM is used to estimate Measurement Models and Structure Models of multivariate theory problems. The SEM model test results are compatible with the collected data when the indexes satisfy the model fit at an acceptable level or higher. To be more precise, $\chi^2/\mathrm{df} < 5$; CFI > 0.9; TLI > 0.9; RMSEA < 0.8.

Finally, we use the Multilayer Perceptron (MLP) to examine the significance of investigated factors in our research models. Multilayer Perceptron (MLP) is an artificial neural network used to model and solve many complex research problems. A general MLP network is one with n ($n \geq 2$) layers (usually the input layer is not taken into account): which consists of an output layer (nth layer) and ($n - 1$) hidden layer. This deep learning method supports generating more accurate results than traditional ones without input assumptions.

### *3.2. Variables and Research Model*

By inheriting the research of Giotopoulos et al. [141], in this paper, we measure Industry 4.0 technologies adoption by a vector of four dependent variables (ITA), including (i) Industry 4.0 technologies intention; (ii) Industry 4.0 technologies infrastructure; (iii) Digitalization; and (iv) 4.0 E-sales. The variables are described as follows.

(i) Industry 4.0 technologies intention (ITA1) is the ordinal variable representing the firm’s willingness to adopt and implement actions related to Industry 4.0 technologies. ITA1’s value scales from 1 (if the enterprise does not take any related action) to 5 (if the enterprise is a pioneer in applying Industry 4.0 technologies).

(ii) Industry 4.0 technologies' infrastructure (ITA2) is an ordinal variable representing the amount of Industry 4.0 technologies' resources, such as technology resource management system, Industry 4.0 technologies manager, computer room, digitalization department, and security solutions within the following year. ITA2's value is from 1 (if the enterprise has no Industry 4.0 related resources) to 5 (if it has already or will deploy all necessary resources to adopt 4.0 technologies within the next year).

(iii) Digitalization (ITA3) is the ordinal variable representing the firm's degree of digitalization through the number of business functions supported by Industry 4.0 technologies as of next year. The variable is scaled from 1 (if no business functions are supported) to 5 (if more than six are supported).

(iv) Industry 4.0 E-sales (ITA4) is the ordinal variable representing the ratio of online selling supported by Industry 4.0 technologies (mobile sale, chatbot, AI, and . . . .) to the total turnover. The variable takes value from 1 (if there is no online selling supported by Industry 4.0 technologies) to 5 (if the ratio of online selling supported by Industry 4.0 technologies to total turnover is over 60%).

According to the conceptual framework of Industry 4.0 technologies adoption proposed in Figure 1, we divide the explanatory variables into five groups: Perceived Technology characteristics (PTC), Technological Competencies (TCAC), Internal organization (CEO), Environmental Characteristics (EC), and Subjective norms (SN).

As regards Perceived technologies (PTC), we use three variables which are Perceived relative advantage (PTC1—The degree to which Industry 4.0 technologies are seen as better than the idea, program, or product it replaces); Perceived compatibility (PTC2—How consistent the Industry 4.0 technologies are with the values, experiences, and needs of the firm); and Perceived trialability (PTC3—The extent to which Industry 4.0 technologies can be tested or experimented with before any adoption commitment).

The vector of Technological competencies (TCAC) is proxied by four variables, including Organizational innovation (TCAC1—number of improvements or innovations that have been realized in the firm's function during the last three years); R and D activities (TCAC2—the percentage of technologies/products/systems used by the firm as a result from internal R and D or R and D collaborations); Personnel with scientific background (TCAC3—the percentage of the firm's employees has a scientific background); and Personnel with ICT skills (TCAC4—The percentage of the firm's employees use ICT skills to the firm's total staff).

As regards CEO characteristics (CEO), we use four variables: Decentralized decision making (CEO1—how decentralized the CEO's decision making process is); Visionary leadership (CEO2—to what extent the CEO/manager is committed to achieving specific growth targets); CEO IT knowledge (CEO3—how knowledgeable the firm's CEO/manager/owner is); and CEO innovativeness (CEO4—how innovative the firm's CEO/manager/owner is).

The vector of Environmental Characteristics (EC) includes four variables: Competitive pressure (EC1—the degree of competitive pressure in the firm's environment); Market turbulence (EC2—the degree and frequency of changes over time that occur to the firm's environment); Institutional intervention (EC3—the degree of Industry 4.0 technologies' support from the government to the firm's environment); Technology spillover (EC4—the perceived degree of Industry 4.0 technologies adoption in the firm's business environment).

We also add control variables for business and environment characteristics, including the firm's size, age, status, and industry. In particular, there are three business size groups: under 200 employees, 200–500 employees, and over 500 employees. There are three age groups: under ten years of establishment, from ten to thirty years of establishment, and over thirty years of establishment. We also control by three firms' statuses, including state-ownership, private local, and foreign firms. Finally, we also control the impact of investigated factors by industry (primary sector, manufacturing, construction, and trade and services. The inclusion of control variables is intended to consider whether the impact of research factors on Industry 4.0 technologies adoption varies depending on firm size, age, industry, and status.

The variables are described in Appendix C.

The quantitative model established to study the factors affecting Industry 4.0 technologies adoption is presented as follows:

$$\mathbf{ITAi = \beta 1PTCi + \beta 2TCACi + \beta 3CEOi + \beta 4ECi + \beta 5SNi + \beta 6Controli + \varepsilon i.}$$

Parameters $\beta$ denote the marginal effects to be estimated. Then, $\varepsilon i$ is the random error term.

### 3.3. Research Data

The study uses primary data surveyed from May 2022 to November 2022. The research data collection process is divided into four steps. First, we built a draft questionnaire based on related theories and previous studies. Second, we sent it to consult and discuss with 12 experts and 20 large business managers with relevant experience in technology and innovation adoption. After receiving appropriate comments, we adjusted the questionnaire accordingly before collecting preliminary quantitative research data on a small sample in the third step. We randomly distributed 170 survey questionnaires to managers working at 170 enterprises, then preliminarily assessed the data fit, reliability, and scale of the sample using SPSS. The final survey questionnaire is defined at the end of step 3 before conducting the official investigation phase in step 4. We listed Vietnamese firms by industry, including Primary sector, Manufacturing, Construction, Trade and Services, according to the Cafef website (https://cafef.vn, accessed on 3 May 2022). Then, we randomly selected and distributed 150 face-to-face and 403 online surveys via email (Google Form) to 553 representatives (General Director, Director, Head of Department, or Management of Science and Technology/IT Department) of Vietnamese companies in different industries.

We took only one valid response as a representative sample of one company to be included in the analysis. The sample consists of various groups of enterprises from diversified business sizes, different production and business experience levels, divergent industries, or various types of business statuses. After eliminating answers with incomplete or wrong information, the remaining sample has 396 companies.

According to Hair et al. [142], the sample size needs to be considered concerning the number of estimated parameters. If using the Maximum Likelihood method (ML), the sample size must be at least 100 to 150. In addition, according to Bollen [143], there must be a minimum of five observations per estimator (ratio 5:1). The study uses 23 observed variables, so the minimum sample size required by this method is 115. On the other hand, according to Raykov and Widaman [144], SEM requires a large sample size because it is based on the large sample distribution theory. Previous studies show that a sample size of 300 is good, 500 is very good, and 1000 is excellent [145]. Thus, the sample size of 396 is sufficient to ensure the reliability and high representativeness of the population.

The measurement of observed variables is described in Appendix C.

## 4. Research Results

### 4.1. Descriptive Statistics

The descriptive statistics are presented below in Table 1. After eliminating 157 inappropriate responses, the study obtained 396 valid samples. Among 396 surveyed subjects, 10.9% of total firms having a labor size of fewer than 200 people (N = 43), firms with a labor size of 200–500 people account for the most significant proportion (48.2%, N = 191), and the rest are enterprises with over 500 employees. Regarding the firms' age, most enterprises in the sample are under 30 years old, accounting for 81.5%, of which 41.9% are enterprises established for less than ten years (N = 166). There are 73 enterprises established over 30 years, accounting for 18.4%. By industry, the number of firms performing in the construction industry accounted for the highest proportion (47%, N = 186), followed by the trade and services industry companies with 36.6% (N = 145). The primary sector and manufacturing industry figures have roughly the same share, at 7.1% and 9.3% (N = 28 and N = 37, respectively). Regarding the firm's status, there are 44.9% foreign businesses (N = 178) and

43.9% private local businesses (N = 174). The number of state-ownership enterprises in the sample accounts for a minor proportion, only 11.1% (N = 44).

**Table 1.** Descriptive statistics.

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| SIZE | | | | |
| <200 employees | 43 | 7.8 | 10.9 | 10.9 |
| 200–500 employees | 191 | 34.5 | 48.2 | 59.1 |
| >500 employees | 162 | 29.3 | 40.9 | 100 |
| Total | 396 | 71.6 | 100 | |
| AGE | | | | |
| <10 years | 166 | 30 | 41.9 | 41.9 |
| 10–30 years | 157 | 28.4 | 39.6 | 81.6 |
| >30 years | 73 | 13.2 | 18.4 | 100 |
| Total | 396 | 71.6 | 100 | |
| INDUSTRY | | | | |
| Primary sector | 28 | 5.1 | 7.1 | 7.1 |
| Manufacturing | 37 | 6.7 | 9.3 | 16.4 |
| Construction | 186 | 33.6 | 47 | 63.4 |
| Trade and Services | 145 | 26.2 | 36.6 | 100 |
| Total | 396 | 71.6 | 100 | |
| STATUS | | | | |
| State-ownership | 44 | 8 | 11.1 | 11.1 |
| Private local | 174 | 31.5 | 43.9 | 55.1 |
| Foreign | 178 | 32.2 | 44.9 | 100 |
| Total | 396 | 71.6 | 100 | |

Source: Calculated from SPSS 24.0 software.

### 4.2. Test of Composite Reliability, Convergent, and Discriminant Validity

Table 2 shows the results of the scale reliability analysis, corresponding to six factors in the model: Perceived Technology characteristics, Technological Competencies, CEO characteristics, Environmental Characteristics, Subjective norms, and Industry 4.0 technologies adoption. It indicates that the scales are reliable because Cronbach's Alpha coefficients are all greater than 0.75 [146]. Indeed, Cronbach's Alpha coefficient values range from 0.756 to 0.883, so these observed variables are accepted.

**Table 2.** Scale reliability analysis.

| Factors | Items | Scale Mean If Item Deleted | Scale Variance If Item Deleted | Corrected Item-Total Correlation | Cronbach's Alpha If Item Deleted | Cronbach's Alpha |
|---|---|---|---|---|---|---|
| Perceived Technology Characteristics | PTC1 | 6.72 | 1.717 | 0.596 | 0.662 | 0.756 |
| | PTC2 | 6.72 | 1.759 | 0.574 | 0.686 | |
| | PTC3 | 6.76 | 1.666 | 0.586 | 0.673 | |
| Technological Competencies | TCAC1 | 9.50 | 3.111 | 0.635 | 0.795 | 0.830 |
| | TCAC2 | 9.35 | 3.002 | 0.660 | 0.784 | |
| | TCAC3 | 8.87 | 2.847 | 0.708 | 0.761 | |
| | TCAC4 | 8.78 | 2.924 | 0.628 | 0.799 | |
| CEO characteristics | CEO1 | 9.62 | 3.016 | 0.639 | 0.803 | 0.834 |
| | CEO2 | 10.10 | 3.207 | 0.640 | 0.800 | |
| | CEO3 | 9.68 | 3.085 | 0.704 | 0.772 | |
| | CEO4 | 9.55 | 3.165 | 0.676 | 0.785 | |
| Environmental Characteristics | EC1 | 10.14 | 3.398 | 0.638 | 0.807 | 0.836 |
| | EC2 | 10.17 | 3.516 | 0.670 | 0.791 | |
| | EC3 | 10.19 | 3.418 | 0.668 | 0.792 | |
| | EC4 | 10.20 | 3.564 | 0.697 | 0.781 | |

**Table 2.** *Cont.*

| Factors | Items | Scale Mean If Item Deleted | Scale Variance If Item Deleted | Corrected Item-Total Correlation | Cronbach's Alpha If Item Deleted | Cronbach's Alpha |
|---|---|---|---|---|---|---|
| Subjective Norms | SN1 | 10.12 | 4.181 | 0.627 | 0.895 | 0.883 |
| | SN2 | 10.13 | 4.069 | 0.719 | 0.859 | |
| | SN3 | 10.11 | 3.939 | 0.791 | 0.832 | |
| | SN4 | 10.14 | 3.764 | 0.854 | 0.806 | |
| Industry 4.0 Technologies Adoption | ITA1 | 10.17 | 4.057 | 0.732 | 0.793 | 0.851 |
| | ITA2 | 10.13 | 4.271 | 0.657 | 0.825 | |
| | ITA3 | 10.19 | 4.125 | 0.742 | 0.790 | |
| | ITA4 | 10.10 | 4.220 | 0.637 | 0.834 | |

Source: Calculated from SPSS 24.0 software.

The below Table 3 shows that the observed variables all have factor loading coefficients greater than 0.5. There are six extracted factors representing 23 observed variables that are rearranged compared with the originally proposed research model as follows: Factor 1 (Subjective norms); Factor 2 (Technological Competencies); Factor 3 (Environmental Characteristics); Factor 4 (CEO characteristics); Factor 5 (Industry 4.0 technologies adoption); and Factor 6 (Perceived Technology characteristics).

**Table 3.** The Rotated Factor Matrix.

| | Factor | | | | | |
|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** |
| SN4 | 1.022 | | | | | |
| SN3 | 0.830 | | | | | |
| SN2 | 0.721 | | | | | |
| SN1 | 0.533 | | | | | |
| TCAC3 | | 0.834 | | | | |
| TCAC2 | | 0.745 | | | | |
| TCAC1 | | 0.697 | | | | |
| TCAC4 | | 0.661 | | | | |
| EC4 | | | 0.775 | | | |
| EC3 | | | 0.763 | | | |
| EC2 | | | 0.751 | | | |
| EC1 | | | 0.704 | | | |
| CEO3 | | | | 0.831 | | |
| CEO4 | | | | 0.755 | | |
| CEO1 | | | | 0.710 | | |
| CEO2 | | | | 0.667 | | |
| ITA1 | | | | | 0.814 | |
| ITA3 | | | | | 0.770 | |
| ITA2 | | | | | 0.732 | |
| ITA4 | | | | | 0.649 | |
| PTC2 | | | | | | 0.746 |
| PTC3 | | | | | | 0.703 |
| PTC1 | | | | | | 0.693 |

Source: Calculated from SPSS 24.0 software.

In addition, Table 4 illustrates the factor correlation matrix. The results show that the correlation coefficients between all factors have absolute values less than 0.602. Therefore, the factors in the model are differentiated.

**Table 4.** Factor Correlation Matrix.

| Factor | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1 | 1.000 | 0.444 | 0.450 | 0.405 | 0.602 | 0.348 |
| 2 | 0.444 | 1.000 | 0.300 | 0.242 | 0.538 | 0.136 |
| 3 | 0.450 | 0.300 | 1.000 | 0.325 | 0.550 | 0.268 |
| 4 | 0.405 | 0.242 | 0.325 | 1.000 | 0.474 | 0.281 |
| 5 | 0.602 | 0.538 | 0.550 | 0.474 | 1.000 | 0.405 |
| 6 | 0.348 | 0.136 | 0.268 | 0.281 | 0.405 | 1.000 |

Source: Calculated from SPSS 24.0 software.

### *4.3. SEM Model Estimation Results and Bootstrap Testing*

To test the research hypotheses, we performed SEM model estimation. The results of the SEM model estimation are illustrated in Figure 2.

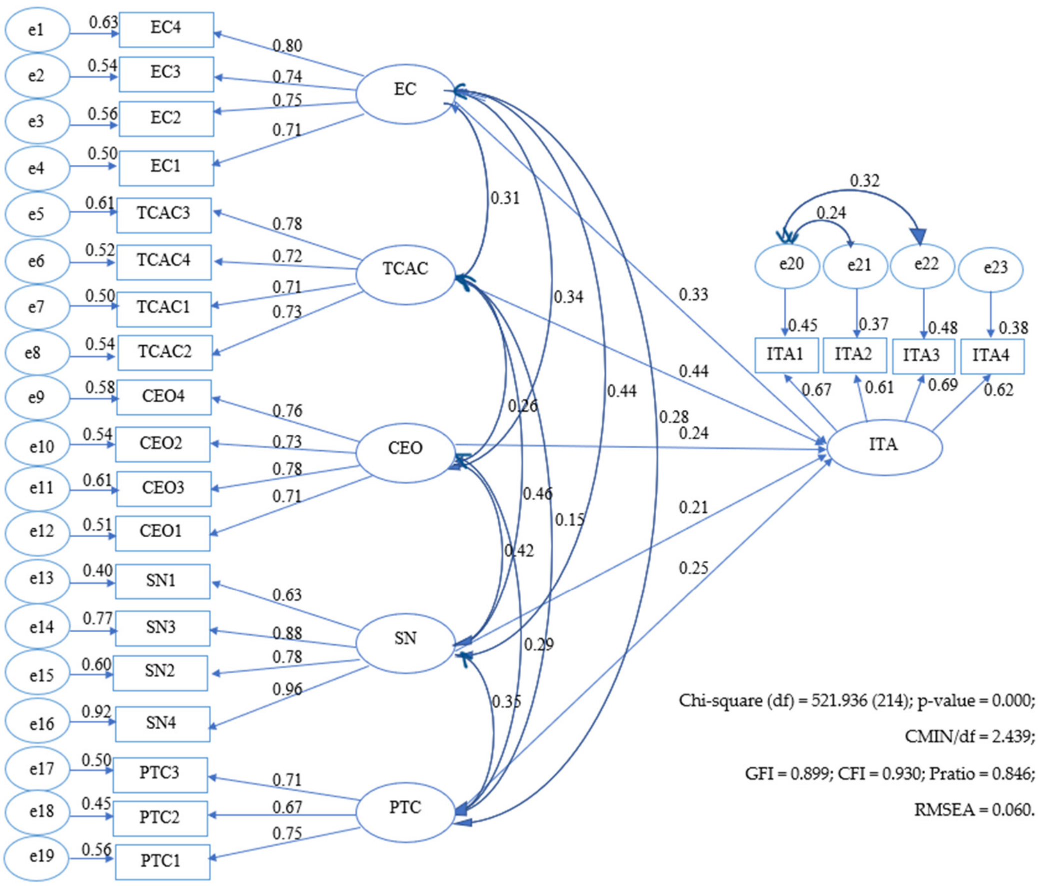


**Figure 2.** The Structural Equation Model. Environmental Characteristics (EC), Technological Competencies (TCAC), CEO characteristics (CEO), Subjective norms (SN), Perceived Technology characteristics (PTC), and Industry 4.0 technologies' adoption (ITA). Source: Calculated from AMOS.

To assess the relevance of the proposed research model, we continue to consider the values of model fit indicators, including AGFI—adjusted goodness-of-fit index; GFI—goodness-of-fit index; NFI—normed fit index; CFI—comparative goodness-of-fit; TLI—Tucker-Lewis Index; and RMSEA—root mean square error of approximation. The results show that the Chi-square/df value of 2439 is lower than the threshold of 3, recommended by McIver et al. [147]. AGFI, GFI, and NFI values are 0.870, 0.899, and 0.888, respectively. For the CFI and TLI indices, the obtained values are all greater than 0.90. The value of the RMSEA index is also within the desired range between 0.05 and 0.08 [148]. Thus, the proposed research model is consistent with the research data.

The estimated results of the parameters reported in the following Table 5 suggest that the five factors Environmental Characteristics (EC), Technological Competencies (TCAC), CEO characteristics (CEO), Subjective norms (SN), and Perceived Technology characteristics (PTC), all have a positive effect on Industry 4.0 technologies adoption (ITA) at the statistical significance level ($p < 0.05$). This means accepting hypotheses H1, H2, H3, H4, and H5.

**Table 5.** Hypothesis Testing with Regression Weights: (Group number 1—Default model).

| | | | Estimate | S.E. | C.R. | *p* | Label |
|---|---|---|---|---|---|---|---|
| ITA | ← | EC | 0.318 | 0.050 | 6.396 | *** | |
| ITA | ← | TCAC | 0.424 | 0.052 | 8.088 | *** | |
| ITA | ← | CEO | 0.244 | 0.050 | 4.860 | *** | |
| ITA | ← | SN | 0.221 | 0.056 | 3.939 | *** | |
| ITA | ← | PTC | 0.242 | 0.049 | 4.966 | *** | |

*** means *p* values less than 0.001. Source: Calculated from AMOS.

Specifically, Technological Competencies positively affect the adoption of Industry 4.0 technologies. This effect is the strongest among the five factors, with a parameter of 0.424. This result implies that the more innovation and R and D enterprises are carrying out, as well as possessing more workforce with a good scientific background and IT knowledge, the more likely firms are to adopt Industry 4.0 technologies. This finding is similar to the suggestions of previous authors [58,61], supporting hypothesis H2.

The impact of Environmental Characteristics on Industry 4.0 technologies adoption was the second strongest, with a parameter of 0.318. In other words, businesses operating in a competitive and rapidly changing environment are likelier to adopt Industry 4.0 technologies. Supportive policies from the government also have the effect of encouraging Industry 4.0 technologies' diffusion. Furthermore, technology spillover also positively impacts the dissemination of Industry 4.0. This result is consistent with previous empirical studies [36,66,98,110], supporting hypothesis H4.

The factors of CEO characteristics and Perceived Technological characteristics have almost the same impact on implementing Industry 4.0 technologies by Vietnamese firms, with parameters of 0.244 and 0.242, respectively. The results regarding the impact of Perceived Technological characteristics are consistent with the theory of Rogers et al. [35]. Meanwhile, the results on CEO characteristics are similar to those of J. Thong [75]. The results of the SEM model support hypothesis H1 and H3.

Subjective norms also have a positive and significant effect on adopting Industry 4.0 technologies in Vietnam, but this impact is the smallest among the factors considered, with a parameter of 0.221. This positive relationship was also reported in previous studies, such as Ajzen [37]'s and Grandón et al. [45]'s supporting hypothesis H5.

Bootstrap Testing

The research then investigates the causal relationship between the research concepts (normalized) and the reliability of the statistical estimates through the Bootstrap 700 test, aiming to estimate the parameters of the statistical study as described in Table 6.

**Table 6.** Testing SEM by Bootstrap 700.

| Parameter | | | SE | SE-SE | Mean | Bias | SE-Bias | CR |
|---|---|---|---|---|---|---|---|---|
| ITA | ← | EC | 0.075 | 0.002 | 0.318 | 0 | 0.003 | 0.00 |
| ITA | ← | TCAC | 0.081 | 0.002 | 0.43 | 0.005 | 0.003 | 1.67 |
| ITA | ← | CEO | 0.081 | 0.002 | 0.242 | −0.002 | 0.003 | −0.67 |
| ITA | ← | SN | 0.081 | 0.002 | 0.217 | −0.004 | 0.003 | −1.33 |
| ITA | ← | PTC | 0.102 | 0.003 | 0.247 | 0.005 | 0.004 | 1.25 |

Source: Calculated from AMOS.

Bootstrap results in Table 6 suggest that the absolute value of CR does not exceed two, which means that the deviation is minimal. Hence, the estimated results in the model can be trusted. The hypotheses H1, H2, H3, H4, and H5 in the research model are accepted at the statistical significance of 95% level ($p < 0.05$).

### *4.4. Analyze the Importance of Variables by Using the MultiLayer Perceptron Model (MLP)*

The SEM estimation results report that the five factors of Environmental Characteristics (EC), Technological Competencies (TCAC), internal organization (CEO), Subjective norms (SN), and Perceived Technology characteristics (PTC) all positively and significantly influence Industry 4.0 technologies adoption. Therefore, we include these five factors in the input layer of the MLP model. The output layer is the vector of Industry 4.0 technologies adoption. In this case, we calculated the number of neurons in the hidden layer and built the MLP model as proposed by Fang and Ma [149], Yao et al. [150], and Panahian [151]. In particular, according to Fang and Ma [149], the number of neurons in the hidden layer will be calculated as $log_2(5) = 2.32$. Hence, we take three neurons in the hidden layer. According to Yao et al. [150] and Panahian [151], the number of neurons in the hidden layer will be calculated as $ln(5) = 1.6$. Thus, the number of neurons in the hidden layer is determined to be 2.

The Sigmoid function is used as the activation function of the neurons in the hidden and output layers. We used 80% of the sample data in this study to train the model. The remaining 20% is used to test the model's accuracy. MLP models are built according to the proposal of Fang and Ma [149], Yao et al. [150], and Panahian [151] as follows (Figures 3 and 4):

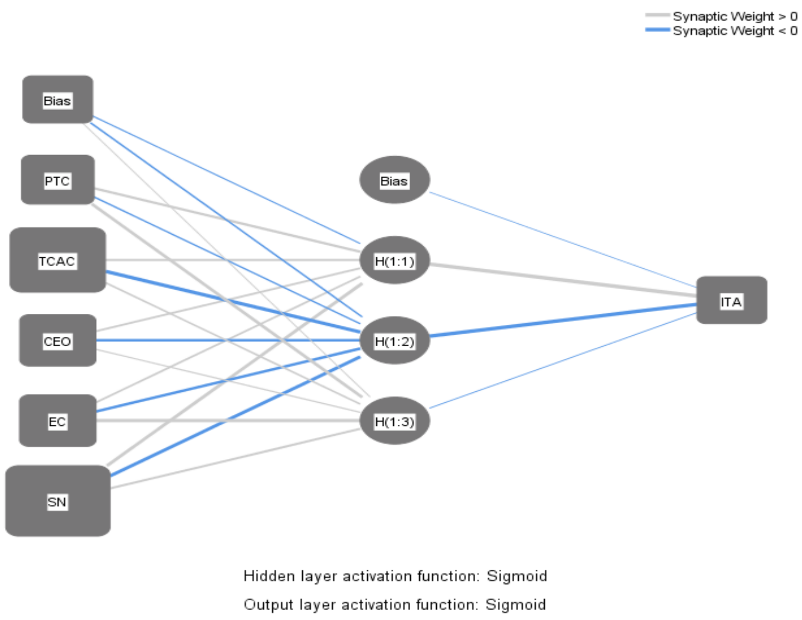


**Figure 3.** MLP model according to Fang and Ma [149]. Source: Calculated from AMOS.

In order to select the most accurate model between the two ones, as mentioned earlier, the study used the accuracy evaluation criteria, including MAE (Mean Absolute Error), MSE (Mean Squared Error), and RMSE (Root Mean Squared Error). The results of the accuracy assessment are presented in Table 7.

**Table 7.** Sum of Squares Error.

| Model | Training Data | Testing Data |
|---|---|---|
| MLP model according to Fang và Ma [149] | 3.068 | 0.938 |
| MLP model according to Yao et al. [150]; Panahian [151] | 2.749 | 1.164 |

Source: Calculated from SPSS 24.0.

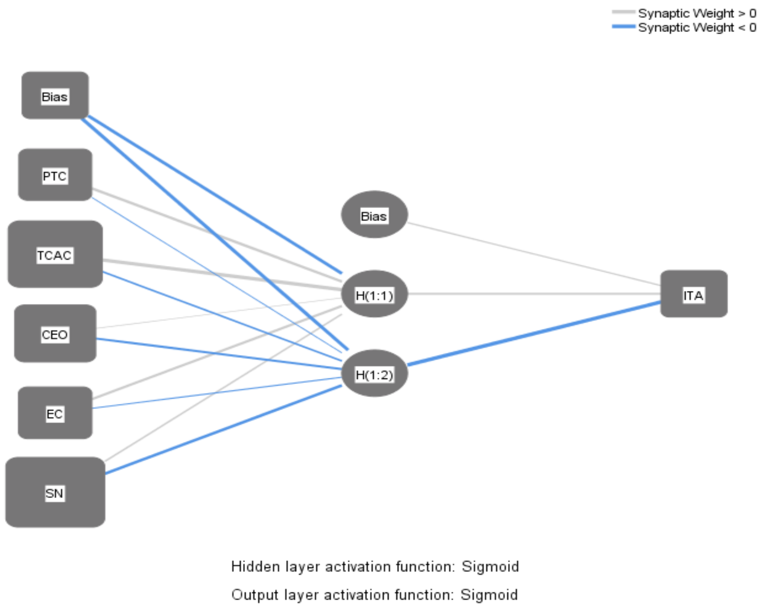


**Figure 4.** MLP model according to Yao et al. [150], and Panahian [151]. Source: Calculated from AMOS.

The results in Table 7 suggest that the MLP model proposed by Yao et al. [150] and Panahian [151] is better than that proposed by Fang and Ma [149]. Therefore, we use the MLP model proposed by Yao et al. [150] and Panahian [151] to identify the importance of factors affecting Industry 4.0 technologies adoption.

The importance of each factor shows how Industry 4.0 technologies adoption will change when this factor changes, as precise in Table 8 as follows.

**Table 8.** The importance of each factor in the MLP model as suggested by Yao et al. [150] and Panahian [151].

| | Importance | Normalized Importance |
|---|---|---|
| SN | 0.258 | 100.0% |
| TCAC | 0.239 | 92.8% |
| CEO | 0.188 | 72.8% |
| EC | 0.159 | 61.5% |
| PTC | 0.156 | 60.6% |

Source: Calculated from SPSS 24.0.

Table 8 reports that the impact of Subjective norms (SN) on Industry 4.0 technologies adoption has the highest importance (100%). Then, the impact of Technological Competencies (TCAC) on Industry 4.0 technologies adoption reaches the second highest importance (92.8%). The importance of the remaining factors is, respectively, CEO characteristics (CEO) (79.5%), Environmental Characteristics (EC) (61.5%), and Perceived Technology characteristics (PTC) (60.6%). Therefore, when controlling the relationship through the MLP model, the impact of these five research factors on Industry 4.0 technologies adoption (ITA) differs from the results obtained from SEM. According to SEM's results, the Technological Competencies factor is the most critical, and the Subjective norms have the slightest impact on Industry 4.0 technologies adoption. Meanwhile, according to the MLP's results, subjective norms have the most powerful and decisive impact on adopting Industry 4.0 technologies in Vietnamese enterprises, pushing the Technological Competencies factor to the second most important position. Moreover, while the environmental characteristics in the SEM model have the second most significant impact on the application of Industry 4.0 technology, it only ranked fourth according to the MLP's results.

### *4.5. Control Variables Analysis*

The following analysis shown in Table 9 examines whether the impact of the research factors on Industry 4.0 technologies adoption depends on the firms' size, age, status, and industry.

**Table 9.** Control variables analysis.

| Control Variables | Test of Homogeneity of Variances's Sig. | Appropriate Test | Sig. |
|---|---|---|---|
| Firm's size | 0.137 | ANOVA test | 0.000 |
| Firm's age | 0.000 | Welch's test | 0.000 |
| Firm's status | 0.171 | ANOVA test | 0.000 |
| Industry | 0.000 | Welch's test | 0.000 |

Source: Calculated from SPSS 24.0.

First, regarding the firm's size, as can be seen from Table 9, the Sig. value of the homogeneity of variances test has a value of 0.137, which is greater than the significance level of 5%. Therefore, the variance between the groups of firms with different sizes is uniform, so ANOVA analysis is suitable to be carried out. Next, the Sig. value of the ANOVA test is 0.000, less than the significance level of 5%. Thus, there is a difference in adopting Industry 4.0 technologies (ITA) between firms of different sizes.

Second, concerning the firm's age, the Sig. v alue of the homogeneity of variances test is 0.000, less than the significance level of 5%. Therefore, the variance between different age groups of firms is not uniform. Hence, we use the Robust Tests of Equality of Means (Welch's test) to evaluate the difference in ITA between firms of different ages. The test result reports that the Sig. value of Welch's test is 0.000, less than the significance level of 5%. Thus, there is a difference in Industry 4.0 technologies adoption between different firms in terms of age.

Third, regarding the firm's status, the Sig. value of the homogeneity of variances test is 0.171, greater than the significance level of 5%. Therefore, the variance between different business groups on status is similar, so ANOVA analysis is conductible. Since the Sig. value of the ANOVA test is 0.000, less than the significance level of 5%; there are differences in Industry 4.0 technologies adoption between the different status of firms (state-ownership/local private/foreign).

Finally, concerning the industry, the Sig. value of the test of homogeneity of variances is 0.000, less than the significance level of 5%. Therefore, the variance among different groups of companies in terms of Industry is not uniform, so we use Welch's test to evaluate the difference in ITA between different firms' industries. The test finding suggests that the Sig. value of Welch's test is 0.000, less than the significance level of 5%, meaning that firms in different industries have different decisions about adopting Industry 4.0 technologies.

## 5. Discussions

### *5.1. Interpretation of Key Findings*

This study explores the factors driving the implementation of Industry 4.0 technologies in Vietnamese companies before identifying the most influential factors. Then, it checks different impacts concerning company characteristics, such as age, size, status, and industry. Thereby, it contributes to the understanding of the factors that facilitate the adoption of Industry 4.0 technologies. The key findings are summarized in Figure 5.

In general, the empirical findings from the SEM model indicate that the higher the absorptive ability, expressed through the higher technological competencies of enterprises, the easier it will be for them to apply 4.0 technologies. Indeed, firms that have carried out R and D and innovation projects have had much experience through learning effects, so they would be willing to adopt new technologies. Moreover, human capital with a scientific background and high IT skills will support businesses to be more confident when applying technological innovations and be ready when encountering problems during the trial phase and implementation. These findings are similar to the previous suggestions of Cohen and Levinthal [58], Hollenstein [61], S. Arvanitis and H. Hollenstein [65], and Ben Khalifa [66] for innovation diffusion and ICT adoption in firms. This similarity could suggest that adopting such complex technologies, such as the Industry 4.0 ones, is not an exception to adopting other previous technologies. An important finding from SEM is that technological competencies have the most decisive impact on applying 4.0 technology in Vietnamese enterprises.

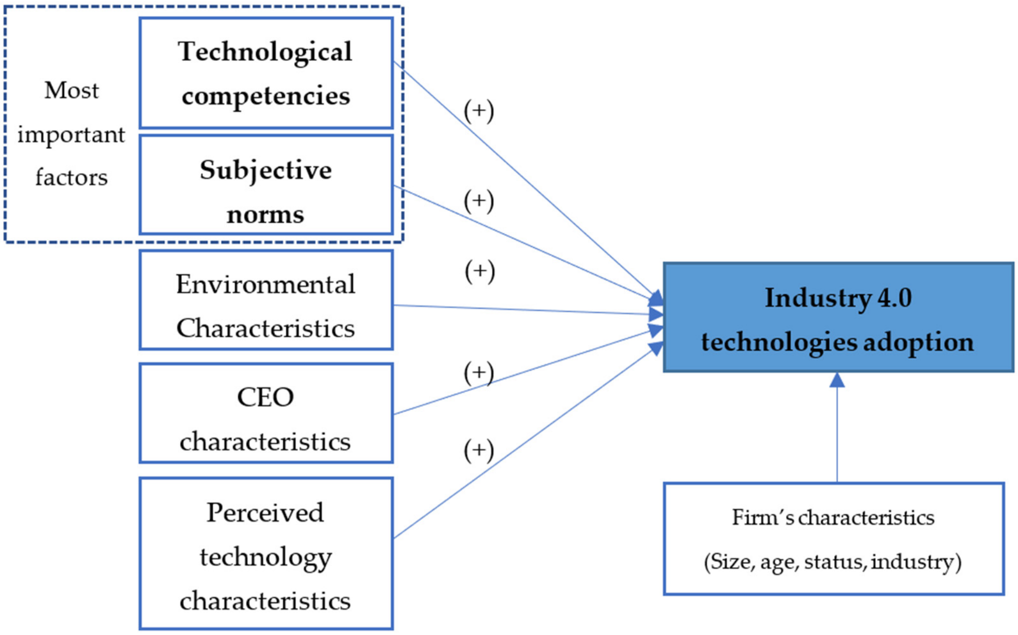


**Figure 5.** Research key findings. Source: Author's compilation.

Moreover, the empirical findings from SEM comply with our theoretical assumption that Environmental Characteristics, CEO characteristics, Perceived Technological characteristics, and Subjective norms have a positive effect on the tendency to implement Industry 4.0. These results imply that businesses operating in a competitive and turbulent environment if led by a CEO with good vision, innovation, decentralized leadership style, and IT knowledge, are more likely to apply technology 4.0, particularly when they realize the benefits and compatibility of these innovations.

Concerning Environmental Characteristics, enterprises urgently need to improve and innovate continuously to maintain a competitive advantage over other competitors in the context of increasingly fierce competition accompanied by unpredictable changes. They also need to actively handle the market's new needs, promptly adjust, and adapt. Industry 4.0 technologies are vital tools that could support businesses in this case, thanks to the ability to increase speed, quality, and efficiency to create innovations and even new products. This result is consistent with previous studies [98,99,103]. In addition, the government's encouragement and support programs (financial, legal, and educational) could create a favorable environment as a driving force for businesses to confidently implement innovation 4.0. This result is similar to the report of Kilangi [110]. In addition, the findings also align with Mansfield's [116] epidemic model. When other businesses in the industry apply 4.0 technologies, firms will become obsolete and lose market share if they do not make improvements. They could face difficulties when exchanging information or working with partners due to technology gaps.

From an organizational perspective, a decentralized structure in the decision making process of companies, along with the presence of visionary, IT-savvy, and innovative leaders, is vital in creating favorable conditions for adopting Industry 4.0 technologies. The decentralized leadership style can motivate subordinates to be empowered and take responsibility for decision making regarding establishing and using new technologies. Therefore, a leader with foresight, ambition to innovate, knowledge, and a solid commitment to growth goals can encourage businesses to apply 4.0 technology in operations and organizational improvements, thereby increasing the ability of the company to expand its boundaries and create new competitive advantages. The research findings are consistent with those of Thong [75], Zappalà et al. [89], and Hansen and Kahnweiler [85].

Regarding Perceived Technological characteristics, the research results are consistent with Roger's [35] suggestion. When firms are aware of the benefits that Industry 4.0 technologies bring to their business, and at the same time find out some suitable technologies for their business models and strategies, firms may consider adopting these innovations. There is a higher probability of adoption for 4.0 technologies, which allows testing before being officially put into practice because firms often wish to check their compatibility and possible risks before investing a large sum.

The results are in accordance with previous studies [37,124] that underlined the importance of Subjective norms for implementing Industry 4.0 technologies in Vietnamese firms. The findings suggest that the promotion and encouragement from people or organizations that are important to the business (a group of shareholders, customers, suppliers, government, or important agents) will make business owners believe that the application of 4.0 technology is necessary, leading to its implementation in practice.

The neural network technique has robust above results from SEM by concluding a positive relationship between these five factors and the adoption of 4.0 technologies in businesses. Even so, the MLP model confirms the absolute importance of subjective norms on Industry 4.0 technologies implementation in Vietnamese firms.

Last but not least, the findings reveal that adopting Industry 4.0 technologies varies regarding firms' size, age, status, and industry, consistent with suggestions from Ben Khalifa [66] and Giotopoulos et al. [141].

### *5.2. Theoretical Contributions*

As previously shown and discussed, this paper contributes to the literature on Industry 4.0 and innovation diffusion by displaying the current state of innovation and Industry 4.0 research and revealing empirical insights from a sample of 396 Vietnamese firms representing various industries.

Although there have been some previous studies on the factors affecting the adoption of Industry 4.0 technologies, most focus on Western countries or leading technology countries, and the literature for developing countries is limited. This research shed light on this critical research gap.

In addition, while previous studies have mainly focused on exploiting data sets belonging to small and medium companies, belonging to a specific industry and/or related to one specific technology [10–14], this study contributes to the theoretical basis by studying the factors affecting the adoption of Industry 4.0 technologies in general based on analyzing the survey data set of enterprises in Vietnam, diverse in size, age, industry, and status. This approach could enhance the generalizability of the results obtained.

The study combines the DOI, TOE, and TPB models to propose a robust explanatory framework for the Industry 4.0 technologies adoption in enterprises, hence contributing to reinforcing empirical evidence from previous related studies. It shows that five factors, including technological competencies, Subjective norms, environmental characteristics, CEO characteristics, and perceived technological characteristics, all positively influence the tendency toward Industry 4.0 technologies adoption. By doing so, several previous studies on similar topics are confirmed, but in the context of Industry 4.0 technologies adoption and in a more contemporary period. Our study is also one of the first to examine the determinants of firms' Industry 4.0 adoption in developing regions, particularly Vietnam.

Moreover, we also approach the topic with the SEM-Neural network, which, to our knowledge, has not been previously used for studies on the same topic. Finally, as a supplementary contribution, the research detects the impact of enterprise status (state-ownership/private local/foreign) on Industry 4.0 technologies adoption, which has not been touched on in the previous literature. So, we suggest assessing the effect of firms' status on technology implementation in further studies.

### 5.3. Managerial Implications

The research results represent critical practical implications for businesses, suggesting essential factors for successfully integrating and using new 4.0 technologies. According to the research findings, technological competencies and subjective norms are the most decisive factors that impact Industry 4.0 technologies adoption in enterprises. Therefore, managers and policymakers need to focus on these two factors.

In the context of a developing country, such as Vietnam, to increase firms' technological competencies, we recommend that firms strengthen R and D and innovation activities and increase workforce training to be ready for the Fourth Industrial Revolution. First, a drastic change in the perception of the firm's managers and staff is needed. Accordingly, it is necessary for them to recognize the critical role of R and D and innovation activities for their sustainable growth so that they could be more active and even more aggressive in investment in R and D activities and 4.0 technology implementation. It should be noted that firms should actively seek and select only technologies suitable for their business strategies and operations to ensure compatibility and maximize technological advantage.

Furthermore, we suggest businesses collaborate with foreign-invested enterprises and those in developed or technological leader countries. These alliances create a favorable condition for Vietnamese firms to grasp new technological standards and access the latest Industry 4.0 technologies, which is considered the most effective shortcut solution. However, Vietnamese enterprises need to be well prepared regarding human resources to achieve maximum absorptive efficiency when receiving new knowledge and technologies. To do that, firms should develop practical training programs in science, technology, and ICT for all levels, from managers to staff. An effective training program requires cooperation with leading local and foreign experts, training units, and leading enterprises in the field. Enterprises can also use government guidelines and policies to support scientific and technological innovation.

However, implementing the above measures may face some challenges in practice. For example, training programs, technology, and associated equipment procurement often require a large amount of investment. At the same time, because Industry 4.0 technologies are new and complicated, the legal corridor is not clear enough, accompanied by operational, security, and technical risks [14,22,99]. These challenges become even more severe for small and medium enterprises. Therefore, government intervention is necessary to promote the application of 4.0 technology in enterprises [110].

Indeed, the government plays an important role in creating a favorable environment for promoting R and D and technological innovation activities, developing a high-quality innovation research and development system, and facilitating cooperation between businesses [110]. The government should have economic support policies, such as tax reduction or credit support for R and D and innovation. In particular, it is necessary to clearly define the priority order for each specific industry corresponding to the country's development orientations. Moreover, combining other policies (such as creating an institutional environment or compensation policy, attracting experts and scientists) is also very important to encourage businesses to improve their technological competencies.

From an educational perspective, the government should facilitate flexible training programs, online courses, or technology 4.0 skills training resources. At the same time, they need to promote the implementation of modules that integrate the knowledge of 4.0 technology in all educational levels (from undergraduate to postgraduate, formal, or informal). They should also consider strengthening relevant support packages or training incentive programs to perform this.

Moreover, the government needs to have policies to encourage FDI attraction and requires FDI enterprises to build reciprocal relationships with other domestic enterprises.

FDI firms should be encouraged to transfer knowledge and new technologies to Vietnamese enterprises to create a compelling and sustainable business ecosystem.

In addition, to take advantage of the impact of subjective norms factor and technological spillover on Industry 4.0 technologies adoption, the government should have "bait mechanisms" to encourage the implementation of Industry 4.0 technologies, with clear specific plans and criteria. Accordingly, they publicly select and support the process of 4.0 technology adoption in some specific enterprises in each industry, which is the starting point for technological spillover afterward. They could also encourage establishing intermediary organizations in consulting and supporting 4.0 technology transfer, along with mechanisms and policies to remove difficulties for pioneering enterprises or innovative start-ups. These policies could promote firms' innovations and are a driving force to encourage other businesses in the industry to implement 4.0 technology.

Last but not least, propaganda activities are indispensable to influencing thoughts and promoting actions to adopt Industry 4.0 technologies in businesses. The government needs to establish a fully updated database that publicly announces guidelines and policies to encourage the adoption of 4.0 technologies, information on activities, research, exchange, and sharing of international and domestic experiences. At the same time, they need to exchange, encourage, and engage the firms' decisionmakers to participate in this effort (due to the additional costs of implementation and maintenance) by convincing them of the benefits of Industry 4.0 technologies in the new era.

### *5.4. Limitations and Future Research*

As with any empirical study, the paper at hand suffers from several limitations that are worth consideration for further research activities. First, the number of surveyed enterprises is not so large due to limited time and finance. Increasing the number of observed samples can improve the accuracy of the results. Second, focusing only on looking at the impact of five factors which are sets of variables on the Industry 4.0 technologies adoption, without considering the specific impact of each variable in that factor, is also a limitation of the study. Third, although the SEM technique is a good method to test their hypotheses, it does not overcome the direction of influence. Then, the survey conducted at a single time point may suffer the common-method bias, so the use of the survey could be addressed as a methodological limitation. Our following study will overcome these shortcomings. In addition, adopting Industry 4.0 technologies depends on different firms' age, sizes, statuses, and industries. So, further research can dig into this in detail. Cross-country studies or comparisons between countries with different economic characteristics to examine if the above effects are different could also be an option for further investigation. Finally, the authors can further consider applying more modern methods to verify the robustness of the proposed model.

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## Appendix A

**Table A1.** Nine pillars of Industry 4.0 according to Boston Consulting Group [28].

| I4.0 Pillars | Definition -Concept |
|---|---|
| Big Data and Analytics | Data analytics based on large data sets to support real-time decision making. |
| Autonomous Robots | Robots that are used in manufacturing are becoming more autonomous, flexible, and cooperative. |
| Simulation | Mathematical modeling, algorithms that optimize the process. |
| Horizontal and Vertical System Integration | Integration of inside of the factory and supply chain. |
| The Industrial Internet of Things | Connection of the physical objects and systems. |
| Cybersecurity | Cyber attacks to business environment. |
| The Cloud | Shared platforms that serve to multiple users. |
| Additive Manufacturing | 3D printing technology, producing in mass customization. |
| Augmented Reality | Human–machine interaction on maintenance tasks. |

Source: Boston Consulting Group (2015).

## Appendix B

**Table A2.** Some technology adoption research.

| Authors | Research Method | Dependent Variables | Independent Variables | Number of Observations | Context |
|---|---|---|---|---|---|
| Giotopoulos et al. [141] | Probit regressions | ICT intentions, ICT infrastructure, Internet integration, E-sales, E-procurement | Organizational innovation, R and D activities, Research collaborations, Personnel with ICT skills, Personnel with scientific background, decentralized decision making, visionary leadership, size, industry, location | 3500 | Survey, Greek SMEs |
| Müller et al. [1] (2018) | Partial least square structural equation model (PLS-SEM) | Industry 4.0 implementation | Strategy, Operations, Environment and people, Competitiveness and future viability, Organizational and production fit, Employee qualifications and acceptance | 746 | Survey, German manufacturing companies |
| Hoyer et al., [13] (2020) | Litterature review | Industry 4.0 implementation/adaptation/readiness | Political support, IT standardization and security, corporate and institutional cooperation, cost assessment and available funding options, available knowledge and education, pressure to adapt, perceived implementation benefits, strategic consideration, IT insfastructure maturity, internal knowledge and skills development, lean manufacturing experience, occupational health and safety, industry sector, size | 246 | Literature review |

**Table A2.** *Cont.*

| Authors | Research Method | Dependent Variables | Independent Variables | Number of Observations | Context |
|---|---|---|---|---|---|
| Horváth & Szabó [12] (2019) | Case study | Industry 4.0 | Data collection and processing, Optimization of the production process, machine—to—machine communication, traceability of production, work without human intervention, preventive maintenance, Visualization, Augmented reality, Intelligent warehousing and logistics | 26 | Interview, SMEs and MNEs |
| Raj et al. [14] (2020) | Grey-DEMATEL Case study | Industry 4.0 implementation | High Investment, Lack of Clarity Regarding Economic Benefit, Value-chain Integration, Risk of Security Breaches, Low Maturity Level of Preferred Technology, Inequality, Disruption to Existing Jobs. Lack of Standards, Regulations and Forms of Certification, Lack of Infrastructure, Lack of Digital Skills, Challenges in Ensuring Data Quality, Lack of Internal Digital Culture and Training, Resistance to Change, Lack of a Digital Strategy Alongside Resource Scarcity | 6 | French and Indian manufacturing firms |

## Appendix C

**Table A3.** Variable notes.

| Variable Set | Variables | Description | References |
|---|---|---|---|
| Panel A: Dependent variable | | | |
| ITA: Industry 4.0 technologies adoption | Industry 4.0 technologies intention | To which extent the company has implemented or intends to implement specific actions to establish Industry 4.0 technologies within the next year. Likert scale from 1 (=absence of related actions or intentions) to 5 (=the firm is a pioneer in the adoption of Industry 4.0 technologies). | [45,66,141] |
| | Industry 4.0 technologies infrastructure | The number of Industry 4.0 technologies resources (information resource management system, information systems manager, computer room, and security back up plan for information systems) in place within the next year Likert scale from 1 (=absence of ICT resources) to 5 (=all relevant ICT resources are available). | [61,141] |
| | Industry 4.0 technologies Digitalization | The number of business functions that are digitalized or supported by the utilization of Industry 4.0 technologies Likert scale from 1 (=no business function supported) to 5 (=more than 6 functions are supported). | [141,152] |
| | E-sales | The ratio of online selling using Industry 4.0 technologies (mobile sale, chatbot, . . . .) to the total turnover. Likert scale from 1 (=no electronic sales) to 5 (=electronic sales represent more than 60% of the total turnover). | [141] |
| Panel B: Independent variables | | | |
| PTC: Perceived Technology characteristics | Perceived relative advantage | Industry 4.0 technologies is seen as better than the idea, program, or product it replaces. Likert scale from 1 (=totally disagree) to 5 (=totally agree) | [35] |
| | Perceived compatibility | The Industry 4.0 technologies are consistent with the values, experiences, and needs of the firm. Likert scale from 1 (=totally disagree) to 5 (=totally agree) | [35] |
| | Perceived triability | Industry 4.0 technologies can be tested or experimented with before a commitment to adopt is made. Likert scale from 1 (=totally disagree) to 5 (=totally agree) | [35] |

**Table A3.** *Cont.*

| Variable Set | Variables | Description | References |
|---|---|---|---|
| TCAC: Technological Competencies/Absorptive capacity | Organizational innovation | How many improvements or innovations have been realized in the firm's function during the last 3 years. Likert scale from 1 (=bsence of innovation) to 5 (=more than 4 innovations). | [35,61,64,66–68,141] |
| | R and D activities | What percentage of technologies/products/systems used by the firm result from internal R and D or R and D collaborations. Likert scale from 1 (=absence of R and D activity) to 5 (=more than 60%). | [55,58,61,64,67–69,141] |
| | Personnel with scientific background | What percentage of the firm's employees has a scientific background. Likert scale from 1 (=no employee with scientific background) to 5 (=more than 60% employees has a scientific background) | [55,74,75,97,141] |
| | Personnel with ICT skills | What percentage of the firm's employees use ICT skills with respect to the firm's total staff? Likert scale from 1 (=no employee with ICT skills) to 5 (=more than 60% employees has ICT skills). | [55,74,75,97,121,141] |
| CEO: CEO characteristics | Decentralized decision making | The decision making process is decentralized. Likert scale from 1 (=totally disagree) to 5 (=totally agree). | [55,61,66,121,141] |
| | Visionary leadership | CEO are committed to achieving specific growth targets. Likert scale from 1 (=totally disagree) to 5 (=totally agree). | [55,64,75,89,121,141] |
| | CEO ICT knowledge | CEO is knowledgeable about ICT. Likert scale from 1 (=totally disagree) to 5 (=totally agree). | [39,41,90–92] |
| | CEO innovativeness | CEO is innovative. Likert scale from 1 (=totally disagree) to 5 (=totally agree). | [15,39,41,89,91] |
| EC: Environmental Characteristics | Competitive pressure | The firm's environment is competitive. Likert scale from 1 (=totally disagree) to 5 (=totally agree). | [96,97,105] |
| | Market turbulence/ Environmental uncertainty | The firm's business environment changes over time. Likert scale from 1 (=totally disagree) to 5 (=totally agree). | [96,98,108] |
| | Institutional intervention/ Government support | The government has made efforts (policies, education, financial supports, . . . ) to encourage the firm's industry to apply Industry 4.0 technologies. Likert scale from 1 (=totally disagree) to 5 (=totally agree). | [110–115] |
| | Industry 4.0 technologies spillover (epidemic effect) | There are Industry 4.0 technologies spillover in the firm's environment. Likert scale from 1 (=totally disagree) to 5 (=totally agree). | [66,116,117] |
| SN: Subjective norms | Important people's thoughts | Most people who are important to my firm think my firm should incorporate Industry 4.0 technologies within the next year. Likert scale from 1 (=totally disagree) to 5 (=totally agree) | [45,128–130] |
| | Influencing people's thoughts | Most people who influence the behavior of my firm think my firm should incorporate Industry 4.0 technologies within the next year. Likert scale from 1 (=totally disagree) to 5 (=totally agree) | [45,128–130] |
| | People whose opinions on firm value | People whose opinions our firm value would prefer our firm to incorporate Industry 4.0 technologies within the next year. Likert scale from 1 (=totally disagree) to 5 (=totally agree) | [45,128–130] |
| | Other firms | Most firms that are important to my firm have adopted Industry 4.0 technologies. Likert scale from 1 (=totally disagree) to 5 (=totally agree). | [45,128–130] |

**Table A3.** *Cont.*

| Variable Set | Variables | Description | References |
|---|---|---|---|
| Control | | | |
| | Firm's size | <200 employees<br>200–500 employees<br>>500 employees | [66,141] |
| | Firm's age | <10 years<br>10–30 years<br>>30 years | [61,66,141] |
| | Firm's status | State-ownership<br>Private local<br>Foreign | [66,153,154] |
| | Industry | Primary sector<br>Manufacturing<br>Construction<br>Trade and Services | [66,141] |

Source: Author's compilation.

## Appendix D

**Table A4.** Literature searching keywords.

| Keywords | Related Words |
|---|---|
| Industry 4.0 technologies | Synonyms: Industry 4.0, The Fourth Industrial Revolution, 4.0 technology<br>Broader words: innovation, technology, ICT, IT<br>Narrower words: Artificial intelligent (AI), big data, Internet of Things (IoT), machine learning, Autonomous Robots, Cloud, cybersecurity |
| Technology adoption | Synonyms: Technology implementation, technology application<br>Broader words: technology diffusion, innovation diffusion, innovation application, innovation adoption, innovation implementation, ICT adoption, ICT implementation<br>Narrower words: Artificial intelligent (AI) (or big data/Internet of Things (IoT)/machine learning/Autonomous Robots/Cloud/cybersecurity), adoption (implementation/application) |
| Vietnamese firms | Synonym: Vietnamese entreprises, Vietnamese companies<br>Broader words: Vietnam<br>Narrower words: Vietnamese SMEs |

Source: Author's compilation.

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