J. Electrical Systems 20-2 (2024): 1128-1141

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Influence Factors of Digital Economy on the Willingness of Equipment Manufacturing Industry to Green Production in the Era of Artificial Intelligence

Abstract: - In the age of artificial intelligence, the digital economy significantly promotes green production in manufacturing. It optimizes processes, recycles resources, drives green tech innovation, and boosts product sustainability. While there's ample research on green manufacturing, studies linking it to the digital economy are limited. Given the machinery manufacturing sector's strategic importance and China's focus on green, sustainable manufacturing, this study bridges that gap. Using the Theory of Planned Behavior (TPB) and Normative Activation Model (NAM), it examines how the digital economy influences green production intentions in equipment manufacturing. The study surveys Middle Eastern equipment manufacturers, analyzes the data with Smart PLS, and finds that the digital economy positively impacts green production via personal norms, responsibility, consequence awareness, attitudes, and cost savings. These factors mediate the relationship between the digital economy and green production intentions. The paper concludes with practical recommendations based on these findings. In the era of artificial intelligence, how the digital economy provides a new path to the green production of the manufacturing industry, and provides a theoretical reference for the sustainable development of the equipment manufacturing industry.

Keywords: Artificial Intelligence, Digital Economy, Equipment Manufacturing Industry, Green Production Willingness, Theory of Planned Behavior (TPB), Normative Activation Model (NAM).

I. Introduction

The arrival of the artificial intelligence era marks our entry into a brand new stage of scientific and technological development, which is based on technologies such as big data, cloud computing and the Internet of Things, and realizes the functions of autonomous machine learning, reasoning and decision-making by simulating the intelligent behaviors and thinking processes of human beings. The wide application of artificial intelligence is profoundly changing our society, economy and lifestyle. And in the field of manufacturing, the promotion of artificial intelligence is particularly significant. For any country, manufacturing stands as a cornerstone of economic development, offering crucial benefits such as job creation, enhanced product quality, improved production efficiency, technological progress, and increased national competitiveness. Over the past few years, China's manufacturing industry has seen rapid growth, establishing itself as one of the world's largest manufacturing nations. Characterized by a large industrial scale, a complete industrial chain, market diversification, continuous technological advancement, and heightened international competitiveness, China's manufacturing sector has made substantial strides. However, it grapples with challenges, particularly concerning environmental impact, highlighting the need for substantial progress toward achieving high-quality and sustainable development.

In the global context, green development has emerged as a prevailing trend and a new focal point for economic growth. Products that align with environmental principles play a pivotal role in the sustained development of the manufacturing industry. For enterprises to ensure long-term stability, the adoption of green production practices is imperative.

Entering the new century, the proliferation of next-generation information technologies such as mobile internet, 5G, industrial internet, and the Internet of Things has ushered in the era of the digital economy. This epoch sees digital information technology driving transformations in production and lifestyle, significantly impacting economic and social development. The digital economy unfolds in two major directions: digital industrialization and industrial digitalization. Integral to this evolution is the intelligent transformation of digital

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product manufacturing and traditional manufacturing. This transformation not only underpins the high-quality development of manufacturing and reinforces the foundation of the real economy but also creates new engines and advantages for national economic development.

In the current economic landscape, the machinery manufacturing equipment industry takes a pivotal role in national development strategies. Implementing green manufacturing and sustainable development is the trajectory for China's manufacturing industry. With a growing focus on environmental consciousness, the green performance of machinery manufacturing equipment is gaining increased attention. The industry's future trajectory hinges on achieving green manufacturing to drive sustainable development. This transformation should align with the characteristics and developmental needs of the manufacturing sector, promoting the synergy of pollution and carbon reduction through digital empowerment to instigate reform.

Simultaneously, the principles of green and low-carbon should permeate the entire product design and production process. While there has been much research on green production in manufacturing, the exploration of the role of the digital economy in the context of artificial intelligence has been relatively limited. Few studies have delved into the interaction between the digital economy and green production in manufacturing. Does the digital economy contribute to environmentally friendly manufacturing? What opportunities and challenges does it present? These are questions deserving of comprehensive investigation.

II. Definition of Related Concepts

A. The Concept of Digital Economy

In recent years, the digital economy has risen as a pivotal subject in academic research, yet a universally agreed-upon concept for it is still in the process of development. In 1996, Don Tapscott, an American scholar, introduced the revolutionary concept of network intelligence. He emphasized that the era of network intelligence encompasses not only the technological aspects of networks but also the interconnectedness of human beings facilitated by technology [1]. Brynjolfsson & Kahin observe that the term "information economy" inherently suggests a sweeping, enduring shift towards the proliferation of information and knowledge-based assets and value, as opposed to tangible assets and products associated with agriculture, mining, and manufacturing [2]. Rouse contends that the "digital economy" constitutes a global network of economic activities bolstered by information and communication technologies. It can also be succinctly defined as an economy primarily reliant on digital technologies [3]. Dahlman et al. assert that the digital economy amalgamates diverse general technologies, constituting a continuum of economic and social activities conducted by people through the Internet and related technologies [4]. As the digital economy continues to advance, it has permeated various industrial sectors, emerging as an increasingly pivotal catalyst for economic growth and emissions reduction [5]. China has implemented a number of new policies such as "Broadband China" and "Internet+" to promote the development of the digital economy [6]. It is widely acknowledged that the digital economy exerts a positive influence on energy efficiency, environmental regulations, and carbon reduction [7]. Lyu et al. posit that the digital economy will serve as the technical bedrock for the Industrial Internet of Things and the consumer Internet. They anticipate the convergence of manufacturing and service industries, predicting a positive trajectory in its long-term development [8].

Therefore, drawing from existing research findings, this paper defines the digital economy as follows: Humans harness the full potential of information and knowledge through the application of digital technology, including industrial Internet, big data, artificial intelligence, and other technologies. Consequently, the digital economy permeates economic and social activities, particularly in the industrial domain addressing energy efficiency, environmental regulation, and carbon emission reduction. Through the advancement of the digital economy, enterprises can attain objectives such as enhancing performance, optimizing supply chain management through intelligent tools, and ensuring effective resource utilization.

B. The Concept of Green Production

Numerous scholars have delved into the definition of green production, with varying perspectives based on their research focus. Taking energy consumption into account, Li Mingyue and colleagues posit that green production embodies a novel manufacturing approach necessitating reduced factor input and high output efficiency. The ultimate objective is to achieve resource conservation, environmental protection, and sustainable development [9]. Considering energy conservation and emission reduction, Guo Quan contends that green production should prioritize source prevention as the primary strategy. Employing advanced technologies and methodologies, it aims to enhance resource utilization, optimize the entire product production process, and achieve efficiency in energy conservation and emission reduction, ultimately enhancing environmental quality [10].Considering energy conservation and emission reduction, Guo Quan contends that green production should prioritize source prevention as the primary strategy. Employing advanced technologies and methodologies, it aims to enhance resource utilization, optimize the entire product production process, and achieve efficiency in energy conservation and emission reduction, ultimately enhancing environmental quality [11]. In summary, the diverse operational procedures, legal frameworks, production methods, and practical applications of products contribute to the varied conceptualizations of green production.

Given that this paper examines the influence of the digital economy on the green production process in the manufacturing sector, it establishes a connection between the digital economy and green production, both guided by the overarching concept of sustainable development. By leveraging emerging digital economic tools such as the Internet of Things, artificial intelligence, and big data, the aim is to attain environmentally friendly and resource-efficient production processes.

C. The Concept of Green Production Will

The concept of green production has been elucidated, emphasizing the suggestion that enterprises should prioritize environmental protection alongside their pursuit of interests. By embracing the ideals of green and sustainable development, this can be achieved through the application of emerging digital economic tools, such as the Internet of Things, artificial intelligence, and big data, to facilitate green and clean production while diminishing resource consumption.

Production willingness, in a general sense, pertains to the proactive intention of entities to center their focus on value creation and dedicate themselves to this purpose. Research on production willingness typically originates from the distinctions among active entities, discerning influencing factors based on individual characteristics, and subsequently formulating countermeasures and recommendations. Therefore, the willingness for green production entails enterprises placing heightened emphasis on environmental concerns amid profit-seeking endeavors. This involves adopting sustainable development as a guiding principle and actualizing green and clean production by leveraging emerging digital economic tools like the Internet of Things, artificial intelligence, and big data. This, in turn, demonstrates the capacity and inclination to curtail resource consumption.

III. Theoretical Background

A. Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB), initially introduced by Ajzen in 1985, posits that an individual's behavior is not solely governed by their volition. Instead, it is intricately linked to the individual's capacity and available resources to execute the intended behavior [12]. The Theory of Planned Behavior (TPB) asserts that all factors capable of influencing behavior do so indirectly through the mediation of behavioral intention [13], In this theory, three fundamental factors play a crucial role, namely behavioral attitude, subjective norms, and perceived behavior control [13]. Since its inception nearly three decades ago, TPB has frequently been employed to comprehend the determinants of various pro-environmental behaviors. For instance, Muñoz et al. investigated the adoption of alternative transportation modes [14], Echegaray and Hansstein studying waste recycling [15], Wei et al. studying low-carbon consumption [16], Moreover, researchers within the country have explored the green production inclination among farmers. Thus, it is justified to employ the TPB theory as the theoretical foundation for this study.

B. Normative Activation Model Theory (NAM)

Normative Activation Model (NAM), introduced by Schwartz in 1977, serves as a framework for forecasting and elucidating individual public environmental behavior. Emphasizing the significance of ethics, it provides insights into a person's prosocial behavior and its impact on pro-environmental intentions [17]. The theory encompasses three key variables: personal norms, attribution of responsibility, and awareness of outcomes. Personal norms are triggered by two conditions—attribution of responsibility and awareness of outcomes—and directly influence the willingness to take action. Additionally, awareness of outcomes indirectly affects personal norms through attribution of responsibility [18]. Due to the interrelation among these three models, numerous studies have been conducted. The Normative Activation Model (NAM) has found extensive application in examining "altruistic" intentions and behaviors across various contexts. Consequently, this paper does not scrutinize the interrelationship among these three models but instead directly explores their impact on green production intentions.

C. Combining Theory of Planned Behavior with Normative Activation Model

Drawing from the pragmatic integration of subjective moral dimensions and objective moral dimensions, this study amalgamates the Normative Activation Model (NAM) with the Theory of Planned Behavior (TPB). While both NAM and TPB are extensively applied across diverse situations, they each exhibit inherent limitations, including relatively low predictive power. Taylor has asserted that a comprehensive understanding of behavior cannot be achieved through reliance on a single theory [19]. Hence, the explanatory power and predictability can be heightened by employing multiple theories. Kim et al. further argue that integrating diverse concepts from competition theory into one or more multi-theory models enables a more effective prediction and understanding of individual behavior [20]. The evolution of theories occurs within distinct research contexts, each emphasizing diverse aspects of social behavior. The integration of theories should stem from their distinctions rather than their similarities.

This study posits that formulating a unified and comprehensive theoretical framework by integrating TPB and NAM will aid in elucidating the intentions of decision-makers. This approach suggests that individuals engage in pro-environmental behaviors, such as green production, not solely driven by personal will and self-interested goals but also influenced by their moral or norm-based perspectives [21].

This indicates that the comprehensive TPB-NAM model incorporates both rational and moral dimensions [22]. The amalgamation of these two models effectively contributes to elucidating the interplay between the conscious features of cognitive factors and the attitudinal characteristics of volitional factors. It also aids in understanding the interaction between the social and normative aspects of volitional factors [23]. It also furnishes a more comprehensive comprehension of the variables influencing decision-makers' inclination to adopt green production.

In existing research, a single theoretical framework is developed by integrating NAM and TBP to assess the adoption of green production in line with the goals of decision-makers within the organization. Therefore, NAM-TPB, established in the context of socially and environmentally responsible behavior and altruistic behavior, will provide a good theoretical framework for elucidating the adoption of green production, as it includes value judgments and cost assessments.

IV. Research Model and Hypothesis Development

Through an extensive review of pertinent literature and empirical research conducted by numerous scholars, this study observes that the fundamental variables of TPB and NAM models offer substantial reference value for understanding the green production inclination within the equipment manufacturing industry. In the course of actual modeling, scholars may adapt the model based on disparities in research objects and content to achieve more precise objectives. To better align the model with the actual research context, this paper will make adjustments accordingly.

Both NAM and TPB are inevitably widely used in pro-environmental behavior research. Therefore, NAM is integrated into TPB to explore the green production willingness of China's equipment manufacturing industry. In addition to the core variables in the TPB model, this paper finds through literature review that "cost saving" may also be an influencing factor that affects the willingness of green production in the equipment manufacturing industry. Therefore, this influencing factor is included in the model construction.

The resulting model is shown in Figure 1:

Personal norms refer to feeling a moral obligation to do or avoid specific behaviors [24], In conjunction with the examination of the digital economy, a hypothesis can be formulated: enterprises discover that leveraging the Internet, intelligent software and hardware, and advanced technologies such as big data can effectively reduce costs, enhance efficiency, and simultaneously fulfill environmental preservation objectives. This realization may activate the moral responsibility of enterprises, instigating a sense of obligation to engage in green production. Consequently, the following hypotheses are proposed:

H1: The digital economy positively impacts individual norms

Responsibility attribution refers to the sense of responsibility for not showing the adverse consequences of pro-society [25], In conjunction with the exploration of the digital economy, a hypothesis can be formulated: Enterprises recognize that intelligent technologies, including the Internet, intelligent software and hardware, and big data, can enhance the efficient utilization of resources and address environmental issues. Conversely, the non-utilization of these technologies by enterprises might exacerbate environmental problems, prompting a sense of responsibility and obligation to engage in green production. Therefore, the following hypotheses are posited:

H2: Responsibility for the positive impact of the digital economy

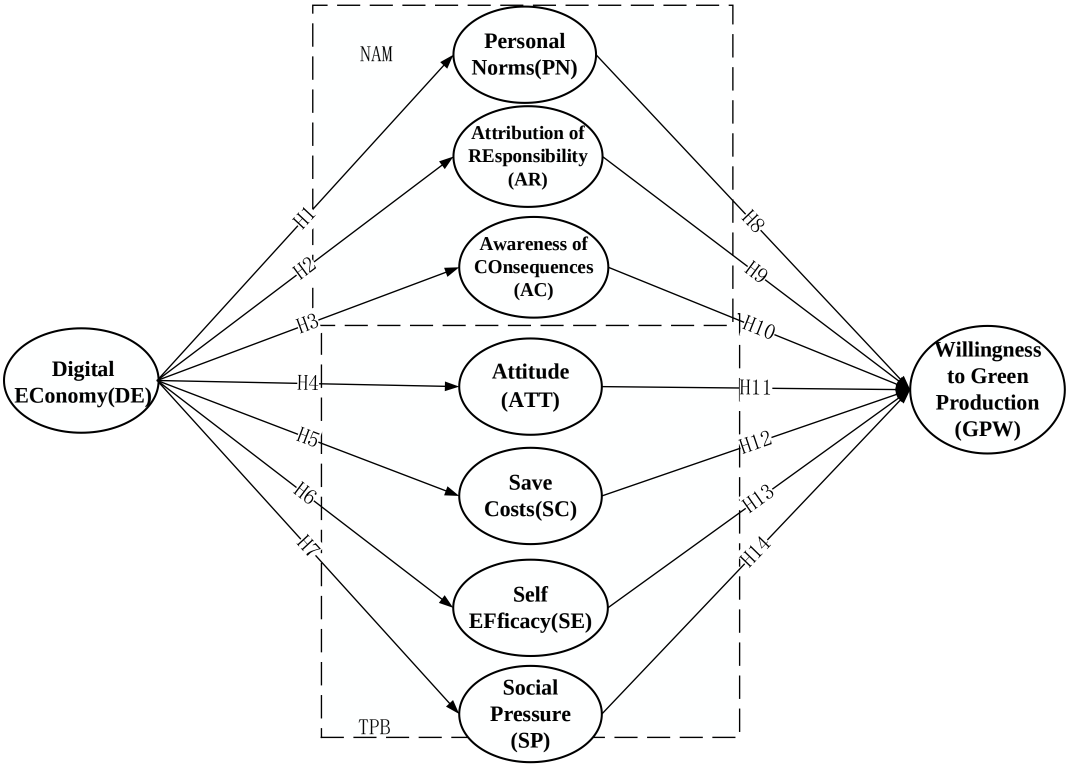

Figure 1: Model of Influencing Factors of Digital Economy on Green Production Willingness of Logistics Equipment Manufacturing Industry

Consequence awareness refers to whether the individual is aware of the negative consequences of others or other things when the individual does not show pro-society[25], In tandem with the examination of the digital economy, a hypothesis can be postulated: Enterprises recognize that intelligent technologies such as the Internet, intelligent software and hardware, and big data can facilitate the efficient utilization of resources and address environmental issues. Conversely, the non-adoption of these technologies by enterprises might exacerbate environmental problems, triggering a sense of responsibility and compelling enterprises to engage in green production. Therefore, the hypothesis is formulated as follows:

H3: Awareness of the consequences of the positive impact of the digital economy

Attitude refers to the extent of personal satisfaction or dissatisfaction with behavior [26], In conjunction with the exploration of the digital economy, a hypothesis can be formulated: Enterprises perceive that intelligent technologies, including the Internet, intelligent software and hardware, and big data, can enhance resource utilization, address environmental issues, and achieve the objectives of cost reduction and efficiency improvement. Consequently, enterprises are likely to exhibit a positive attitude towards green production. Therefore, the following hypotheses are proposed:

H4: The positive impact of the digital economy on attitudes towards green production

Self-efficacy refers to the judgment of an individual's ability to use technology to complete a specific job or task[27], combined with the study of the digital economy, it can be hypothesized that enterprises find that intelligent technologies such as the Internet, intelligent software and hardware and big data can promote the effective use of resources, improve environmental problems and achieve the goal of reducing costs and increasing efficiency, but enterprises think that their ability to the company's capital and information functions are slightly insufficient in realizing intelligent technology, which will prompt enterprises to constantly learn and strengthen their judgment. This is conducive to better green production for enterprises. Therefore, hypotheses are made:

H5: The digital economy positively impacts self-efficacy

Self-efficacy refers to an individual's assessment of their capability to utilize technology for a specific job or task[28], In connection with the exploration of the digital economy, a hypothesis can be formulated: Enterprises recognize that intelligent technologies such as the Internet, intelligent software and hardware, and big data can enhance resource utilization, address environmental issues, and achieve goals like cost reduction and efficiency improvement. However, enterprises may perceive a slight inadequacy in their ability to leverage the company's capital and information functions to realize intelligent technology. This perception may prompt enterprises to continuously learn and enhance their judgment, fostering a conducive environment for improved green production. Therefore, the following hypotheses are posited:

H6: The digital economy has a positive impact on cost savings

Social pressure implies that individuals are more likely to engage in a behavior if they perceive support for that behavior from significant others [26]. In conjunction with the understanding of the digital economy, a hypothesis can be formulated: When companies realize that the digital economy can enhance environmental problem-solving, optimize resource utilization, and reduce costs, the advantages will come to the forefront. This may prompt more companies to embrace the digital economy, consequently encouraging the government to formulate positive policies. Such policies, in turn, would support companies in pursuing green production. Therefore, the hypothesis is postulated as follows:

H7: The digital economy positively affects social pressure

In NAM, the initial variable predicting prosocial behavior is personal norms, described as "feeling a moral obligation to do or avoid specific behaviors [24]." Environmental issues undoubtedly necessitate an ethical element of personal responsibility for the environment. A personal norm signifies a specific type of behavior that must be activated before it becomes relevant. Scholars studying pro-environmental intentions, such as Muñoz et al [14] and Echegaray and Hansstein [15]. Assert that pro-environmental intentions are influenced by direct predictors of personal norms. Numerous studies have identified personal norms as the most crucial factors or drivers influencing various pro-environmental behaviors. It is worth noting that there is an association between personal norms and general pro-environmental behaviors. For instance, Zhang Ruizeng and others indicated that personal norms significantly impact the pro-environmental behavior intention of farmers regarding the adoption of green and high-quality agricultural products [29]. Furthermore, Gao Aoyu pointed out that personal norms also have a substantial impact on the pro-environmental behavior of rural residents engaging in the centralized treatment of domestic waste [30]. Therefore, in this study, decision-makers' intentions toward green production will be propelled by personal norms of environmental protection. Policymakers can perceive green production intentions as a means to achieve sustainability and ensure environmental protection. Therefore, the hypothesis is formulated as follows:

H8: Personal norms positively affect the willingness to adopt green production

The Attribution of Responsibility constitutes the second variable in the NAM (Name of the Model) framework, predicting prosocial behavior as the "sense of responsibility for the adverse consequences of not being prosocial"[25]. According to NAM, personal belonging not only shapes one's pro-environmental and pro-social conduct but also serves as a catalyst for moral obligations. Qu Tongtong highlighted that corporate employees, contemplating responsibility attribution in environmental protection behavior, tend to exhibit supportive environmental actions and cultivate a moral obligation to safeguard the environment within the company [31]. Furthermore, Gao Aoyu underscored the importance of responsibility attribution in stimulating individual moral obligations and instigating pro-social intentions [30]. Consequently, it is plausible to hypothesize that when managers attribute responsibility to themselves for mitigating environmental threats, they are more inclined to adopt green production practices and feel a heightened obligation to engage in pro-environmental behaviors. Thus, the hypothesis is formulated as follows:

H9: Responsibility attribution positively affects the willingness to adopt green production

Consequence awareness emerges as the third variable in the NAM framework, serving as a predictor of prosocial behavior and defined as "whether an individual is cognizant of the negative consequences for others or the environment when they fail to exhibit prosocial behavior" [25]. To illustrate, individuals who acknowledge the adverse environmental impact of car usage are likely to harbor a stronger moral obligation to curtail their use of cars compared to those oblivious to such consequences. Numerous studies, including those conducted by Qu Tongtong [31], Gao Aoyu [30], Shahla, Asadi et al. [32], have consistently revealed a positive correlation between understanding adverse repercussions and pro-environmental behavior. Moreover, awareness of consequences proves to be a pivotal factor in prosocial behavior and intentions. Consequently, if managers possess heightened awareness of the potential adverse consequences of environmental conditions, their sense of obligation to adopt pro-environmental behaviors increases, consequently elevating their likelihood of intending to embrace green production. Therefore, the hypothesis is posited as follows:

H10: Consequence awareness positively affects the adoption of green production

Attitude, defined as "the degree to which an individual evaluates a behavior as satisfactory or unsatisfactory"[26], holds significant sway in the realm of green production. Attitudes towards green production play a pivotal role in fostering sustainable development. Indeed, attitudes serve as a precursor to the decision-making process, influencing the choice to embrace new practices such as green production [33] additionally, attitudes are recognized as one of the primary drivers shaping the adoption of technology [34].

The attitudes of management wield considerable influence over goal-setting and subsequent outcomes [35]. The emotional disposition of organizational decision-makers reflects their attitude, serving as a gauge of their interest and commitment to environmentally conscious practices. A positive attitude among decision-makers is deemed a prerequisite [36]. Furthermore, in the prediction of behavior, attitudes towards specific actions emerge as the most reliable indicators [37]. Subsequent research in information systems and social psychology has corroborated the robust predictive nature of attitudes in forecasting intentions to adopt green production[38]. Therefore, the following hypotheses can be formulated:

H11: Attitudes towards green production positively influence the willingness to adopt green production.

In the traditional Theory of Planned Behavior (TPB), "self-efficacy" is akin to "perceived behavioral control." Specifically, self-efficacy is defined as "an individual's judgment of their ability to utilize technology effectively in accomplishing a specific job or task" [27]. The decisions and choices made by individuals are notably influenced by self-efficacy, as individuals tend to engage and excel in tasks they believe they can successfully execute [39]. Furthermore, individuals with a high level of self-confidence view complex challenges as opportunities rather than perceiving them as threats to be avoided [40]. Shahla Asadi et al. explored the Malaysian manufacturing industry using the NAM-TPB integrated research framework, employing self-efficacy as a predictive factor for managers' inclination to embrace green IT [32].

Self-efficacy has demonstrated its impact on behavior and behavioral intent in various contexts, including environmental domains such as recycling [15], and counter-environmental behavior like excessive use of plastic bags [41]. Consequently, for environmental concerns, the study posits that the self-efficacy of policymakers, exemplified by managers' confidence in possessing the fundamental knowledge, skills, and competencies to address environmental issues, strongly correlates with their willingness to adopt green production. Therefore, the hypotheses are formulated as follows:

H12: The higher the level of self-efficacy, the more positive the willingness to adopt green production

Cost savings encompass the reduction in capital investment required by a business for services, resource leasing, and hardware solutions [28]. Recognizing the tangible advantages of green production initiatives, organizations have integrated cost savings as a crucial element into the Theory of Planned Behavior (TPB). Many enterprises have come to realize that embracing green production not only contributes to environmental benefits in terms of support, management, procurement, and energy use but also yields significant cost-saving advantages [42]. In fact, some organizations adopt green strategies primarily to achieve cost savings [43]. Practitioners increasingly focus on green production with a predominant emphasis on eco-efficiency, with the realized benefits emanating from both cost savings and enhanced energy efficiency [44]. Shahla Asadi et al. observed that economic benefits, particularly cost savings, are frequently cited as significant factors in the adoption of green production [32]. Therefore, as a result of rational analysis, cost savings become a pivotal component in the TPB theory. The higher the level of cost savings, the greater the inclination toward green production. Hence, the hypotheses are as follows:

H13: Cost savings will positively influence managers' willingness to adopt green productionIn the standard TPB, "social pressure" is "subjective norms".

Social pressure denotes that individuals are more inclined to engage in a particular behavior when they perceive support from significant others. For instance, when the government places a high value on green development and implements various preferential policies, it serves as a catalyst for enterprises to actively embrace green production. Consequently, the following hypotheses are posited:

H14: Social pressures influence their willingness to adopt green production

V. METHOD

Building upon existing research and the current research landscape, the questionnaire is structured into two distinct sections. The first segment primarily focuses on gathering respondent information, encompassing details such as gender, age, position level, education level, and other relevant demographics. The second part delves into investigating the factors influencing the willingness of the digital economy to engage in green production within the equipment manufacturing industry.

Aligned with the scale design outlined in the preceding section, this study employs the Likert five-point scale. Respondents are instructed to provide scores on a scale ranging from "1-5," corresponding to the circumstances within their respective enterprises. It is important to note that all questions are mandatory, and the questionnaire cannot be submitted unless every question is addressed. Following the initial questionnaire design, we sought input from experts in relevant fields for a comprehensive review and conducted a small pre-test to refine the questionnaire.

Once the questionnaire was finalized, meticulous attention was given to the distribution and collection processes. The survey targeted the equipment manufacturing industry in the Middle East region, with respondents comprising management personnel at various levels, both direct and indirect. A total of 430 questionnaires were distributed to equipment manufacturing enterprises in the Middle East of China. Subsequently, 390 questionnaires were retrieved, and after careful screening, 366 valid questionnaires were obtained. This resulted in a robust recovery rate of 90.70% and an impressive questionnaire effectiveness rate of 93.85%.5.2. Measurement Model Results

The methodology employed in this study utilizes structural equations, encompassing two distinct methods: covariance-based structural equation modeling (CB-SEM) and variance-based structural equation modeling (PLS-SEM). Specifically, this study employs VB-SEM, utilizing Partial Least Squares SEM (PLS-SEM), along with the corresponding software package (SmartPLS 4.0). PLS-SEM, a second-generation multivariate data analysis method, is predominantly applied in exploratory theoretical research. This method ensures the integrity of relationships between all independent and dependent variables. In contrast to CB-SEM, PLS-SEM offers several advantages. Firstly, it is more suited for models involving latent variables. Secondly, it excels in handling small sample data and exploratory research. Thirdly, PLS-SEM effectively manages non-normally distributed data. In summary, during the theoretical development stage, the PLS-SEM method proves more applicable than the CB-SEM method. In the majority of social science research cases, PLS-SEM can effectively replace CB-SEM and is widely employed in studies within the realms of social, economic, and business research.

This study is of an exploratory nature, featuring nine latent variables within the study model and a relatively small effective sample size. Furthermore, a multivariate normality analysis was conducted on the collected data using a web calculator (https://webpower.psychstat.org/, accessed on 14 March 2023). The results revealed that Mardia's multivariate skewness (β = 130.5334, $p > 0.05$) and multivariate kurtosis (β = 1325.9070, $p < 0.01$) indicated the presence of multivariate nonnormality. In conclusion, PLS-SEM emerges as a more suitable approach for data analysis in this study.

VI. Results

A. Common Method Bias Test

To assess the absence of response bias, we conducted a t-test comparing the first 25 respondents with the last 25 investigators. The test results revealed no significant difference, indicating that non-response bias is not a significant concern.

Table 1: VIF

	VIF		VIF
PN 1	1.584	SE1	1.731
PN2	2.333	SE2	2.713
PN 3	2.945	SE 3	2.568
PN 4	1.988	SE4	1.824
AC 1	1.822	CS 1	2.012
AC 2	2.707	CS 2	2.808
AC3	2.396	CS 3	2.612
AC4	1.736	CS4	1.874
DE 1	2.147	SP 1	1.617
DE 2	2.896	SP 2	2.345
DE 3	2.475	SP 3	2.610
DE 4	1.822	SP4	1.940
GPW 1	1.272	ATT1	1.807
GPW 2	1.727	ATT 2	2.708
GPW 3	2.043	ATT3	2.987
GPW 4	1.560	ATT4	2.006
AR 1	1.941	AR 3	2.292
AR 2	2.675	AR 4	1.779

In addition to investigating non-response bias, we also examined the presence of common method bias (CMB) using two measurement methods. Firstly, the study employed the univariate extraction rate measured through SPSS software, following the approach suggested by Podsakoff et al.[45], the calculated rate, at 37.747%, falls below the 50% threshold. Secondly, a comprehensive measurement of variance inflation factor (VIF) was conducted to identify common method deviation (CMB) in PLS-SEM. All VIF values in this study are equal to or lower than 3.3, as detailed in Table 1, suggesting the absence of common method deviation in the model. The results from both tests indicate that CMB is not a significant concern in this study.

B. Measurement Model Results

Firstly, comprehensive reliability is employed to assess internal consistency reliability. In this experiment, the external load, average variance extraction (AVE), and composite reliability of the items were analyzed, and the results are presented in Table 2 and Table 3. Following the recommended criteria by Hair et al.[46], the external loading (Loading) on the project should exceed 0.5, the composite reliability (CR) for each structure should surpass 0.7, and Cronbach's α should also be greater than 0.7.

As depicted in Table 2, the minimum average external load for the project is 0.545, meeting the specified criterion. Table 3 reveals that the minimum value of composite reliability (CR) for each structure is 0.825, satisfying the requirements. Additionally, Cronbach's α (CA) has a minimum value of 0.758, which also meets the stipulated criteria. These findings indicate that the questionnaire items demonstrate high reliability.

Secondly, this study establishes convergent validity by assessing average variance extraction (AVE). AVE values exceeding 0.5 are considered indicative of satisfactory convergent validity [46]. In the model results, the minimum AVE value is 0.531, affirming the good convergent validity of the questionnaire.

Table 2: Item External Loads for Variables

	Item	Loadings		Item	Loadings
PN	PN1	0.841	SE	SE1	0.851
	PN2	0.862		SE2	0.892
	PN3	0.794		SE3	0.737
	PN4	0.607		SE4	0.602
AC	AC1	0.847	CS	CS1	0.872
	AC2	0.901		CS2	0.901
	AC3	0.745		CS3	0.807
	AC4	0.584		CS4	0.679
DQ	DE1	0.782	SP	SP1	0.864
	DE2	0.888		SP2	0.867
	DE3	0.864		SP3	0.756
	DE4	0.738		SP4	0.603
GPW	GPW1	0.870	ATT	ATT1	0.860
	GPW2	0.764		ATT2	0.892
	GPW3	0.697		ATT3	0.803
	GPW4	0.545		ATT4	0.645
AR	AR1	0.876	AR	AR3	0.710
	AR2	0.904		AR4	0.588

Table 3: Reliability and Convergent Validity of Variables

	Cronbach's α	CR	AVE
PN	0.806	0.861	0.612
AC	0.800	0.857	0.606
DQ	0.836	0.891	0.673
GPW	0.758	0.815	0.531
AR	0.809	0.858	0.609
SE	0.806	0.858	0.607
CS	0.846	0.890	0.671
SP	0.812	0.859	0.608
ATT	0.834	0.880	0.649

Thirdly, this study used heterotrait-single-trait ratio (HTMT) to test discriminant validity. According to the suggested value by Hair et al. [46], the value between variables should be less than 0.85. The results are shown in Table 4, the maximum value among variables is 0.836, which meets the requirements.

Finally, this study employs the Fornell-Larcker reflective variables to assess discriminant validity. Following the criteria recommended by Hair et al., the square root of AVE should exceed the correlation coefficient between variables [46]. The specific values are presented in Table 5, indicating that the discriminant validity of the reflective variables in this study is satisfactory. These results indicate that the discriminant validity of the scale in this study meets these requirements.

Table 4: Heterogeneous Trait-single Trait Ratio (HTMT)

	PN	AC	DQ	GPW	AR	SE	CS	SP	ATT
PN									
AC	0.483								
DQ	0.836	0.766							
GPW	0.559	0.496	0.631						
AR	0.559	0.483	0.759	0.470					
SE	0.533	0.427	0.742	0.417	0.451				
CS	0.523	0.481	0.808	0.452	0.472	0.494			
SP	0.568	0.503	0.775	0.430	0.535	0.512	0.509		
ATT	0.606	0.533	0.829	0.491	0.573	0.478	0.545	0.519	

Table 5: Forner11-Larcker

	PN	AC	DQ	GPW	AR	SE	CS	SP	ATT
PN	0.783								
AC	0.538	0.779							
DQ	0.690	0.735	0.820						
GPW	0.613	0.530	0.651	0.729					
AR	0.613	0.562	0.749	0.554	0.780				
SE	0.581	0.497	0.721	0.499	0.527	0.779			
CS	0.569	0.529	0.755	0.536	0.542	0.533	0.819		
SP	0.634	0.581	0.776	0.524	0.589	0.579	0.577	0.780	
ATT	0.649	0.572	0.787	0.578	0.622	0.541	0.584	0.603	0.806

C. Structural Model Results

According to Hair et al. [47], the coefficient (R2), prediction correlation (Q2), and standardized root mean square residual (SRMR) in the data were used to assess the quality and fit of the structural model, and the results are shown in Table 6. The results of the structural model evaluation are interpreted as follows:

(1) R2 represents the proportion of independent variables that can explain the variation in the dependent variable, providing information about the predictive power within the sample [47]. It is generally accepted that around 0.25, 0.5, and 0.75 represent weak, moderate, and strong explanatory power of the independent variable over the dependent variable, respectively [47]. In this study model, the independent variables have strong explanatory power for the R2 = 0.624 of the individual norm. R2 = 0.540 for consequence awareness has moderate explanatory power; R2 = 0.485 of green production willingness has moderate explanatory power; R2 = 0.561 for attribution has moderate explanatory power; R2 = 0.519 of self-efficacy has moderate explanatory power; The cost-saving R2=0.570 has moderate explanatory power; R2=0.602 of social stress has moderate explanatory power; R2=0.620 with a green production attitude has moderate explanatory power.

(2) The Q2 value was proposed by Stone and represents the predictive correlation of known samples to unknown samples [48]. Hair et al. proposed a measure of Q2, that is, around 0.00, 0.25, and 0.50 represent low, medium, and high predictive correlations, respectively [47]. In this study, running the blindfolding program in SmartPLS4.0 yields Q2, and the results show that the independent variable has a moderate prediction of Q2=0.319 for the personal norm; Q2 = 0.272 for consequence awareness has a moderate character; Q2 = 0.281 for self-efficacy has a moderate prediction; The cost-saving Q2 = 0.257 has a medium forecast; Q2=0.289 with green production attitude has a medium forecast; Q2 = 0.334 for social stress has a moderate prediction; R2 = 0.000 for green production willingness has a low prediction; R2 = 0.189 for attribution has a low prediction.

(3) SRMR is used to assess the difference between observational and predicted correlations [49]. According to Hu & Bentler, an SRMR value of less than 0.08 is considered a good fit for the model [49]. The SRMR value of the model constructed in this study is 0.075, which meets the recommended criteria, so it can be considered that the model fits well with the empirical data.

D.The Result of Hypothesis Testing

The path coefficient value (β) is obtained by running the PLS algorithm in SmartPLS4.0, and this coefficient can calculate the VAF value of the mediation effect below. The significance of the estimated value of the path coefficient can be reflected by the T value and P value, which are obtained by the Bootstrapping algorithm.

When the path coefficient T value is greater than 1.96, greater than 2.57 is better [49]. It can be seen from Table 7 that the T values of H1, H2, H3, H4, H5, H6, H7, H8, H9, H10, H11, and H12 are all greater than 1.96, so the path coefficient is significant; while the T values of H13 and H14 are all is less than 1.96, so the path coefficient is not significant.

Table 6: Model Evaluation Results

	R^2	Q^2	SRMR
PN	0.624	0.319	0.075
AC	0.540	0.272	
GPW	0.485	0.000	
AR	0.561	0.189	
SE	0.519	0.281	
CS	0.570	0.257	
SP	0.602	0.334	
ATT	0.620	0.289	

From Table 7, we can see that the digital economy has positive effects on personal norms (0.790, $p < 0.001$), awareness of consequences (0.735, $p < 0.001$), responsibility attribution (0.749, $p < 0.001$), self-efficacy (0.721, $P < 0.001$), saving The effects of cost (0.755, $P < 0.001$), social pressure (0.776, $p < 0.001$), attitude towards adopting green production (0.787, $p < 0.001$) had significant positive effects; thus supporting H1, H2, H3, H4, H5, H6, H7. Personal norms to green production intentions (0.252, $p < 0.001$), consequence awareness to production intentions (0.135, $P<0.05$), attitudes to adopt green production intentions to production intentions (0.139, $P<0.05$), cost saving to production intentions (0.128, $P<0.05$), responsibility attribution has a significant positive effect on production willingness (0.122, $P<0.05$), thus supporting H8, H10, H11, H12, and H14. However, the impact of social pressure on green production intention (0.009, $P>0.05$) and self-efficacy on production intention (0.007, $P>0.05$) is not significant, so H13 and H14 are not supported.

Table 7: Main Path Analysis and Hypothesis Testing Results

	β	STDEV	T	P	Upper	Lower	Result
H1	0.790	0.012	68.637	0.000	0.769	0.814	Support
H2	0.749	0.015	49.974	0.000	0.721	0.779	Support
H3	0.735	0.016	45.417	0.000	0.704	0.766	Support
H4	0.787	0.012	63.578	0.000	0.763	0.812	Support
H5	0.755	0.016	47.778	0.000	0.724	0.786	Support
H6	0.721	0.017	42.841	0.000	0.690	0.754	Support
H7	0.776	0.011	73.552	0.000	0.757	0.798	Support
H8	0.252	0.060	4.214	0.000	0.134	0.366	Support
H9	0.122	0.055	2.222	0.026	0.012	0.223	Support
H10	0.135	0.053	2.535	0.011	0.029	0.239	Support
H11	0.139	0.062	2.255	0.024	0.019	0.261	Support
H12	0.128	0.049	2.604	0.009	0.031	0.224	Support
H13	0.007	0.051	1.325	0.185	0.034	0.164	Reject
H14	0.009	0.055	0.307	0.759	-0.092	0.124	Reject

Table 8: Mediation Effects

	P-Vaue	STDEV	T-Vaue	Indirect effect	Total effect	VAF	Mediation type
DQ→PN→GPW	0.000	0.047	4.282	0.199	0.227	87%	Fully
DQ→AR→GPW	0.026	0.041	2.232	0.091	0.119	76%	Partially
DQ→AC→GPW	0.011	0.039	2.546	0.099	0.127	77%	Partially
DQ→ATT→GPW	0.023	0.048	2.276	0.109	0.137	79%	Partially
DQ→CS→GPW	0.009	0.037	2.603	0.097	0.125	77%	Partially
DQ→SE→GPW	0.185	0.036	1.327	0.005	0.033	15%	No
DQ→SP→GPW	0.759	0.043	0.306	0.007	0.035	20%	No

E. Mediation Effect Test

In this study, we refer to the results of the Hadi study of the Mediation Effect Test, and the strength of the mediating effect is obtained by calculating the ratio of indirect effects to the total effect, that is, the VAF value [50]. Based on experience, scholars believe that VAF values greater than 80% represent complete intermediation, between 20% and 80% represent partial intermediation, and less than 20% represent no mediation effect [50]. After calculation, the results are shown in Table 8: the relationship between the digital economy and green production willingness of the individual normative fully intermediary; the relationship between the responsibility ownership part of the intermediary digital economy and the green production willingness; the relationship between the consequence consciousness and the green production willingness; the relationship between the adoption attitude of the digital economy and the green production willingness; the relationship between the cost-saving part of the intermediary digital economy and the green production willingness.

VII. Discussion and Conclusions

A. Key Findings

The digital economy in the era of artificial intelligence plays an important role in promoting green production in the manufacturing industry [51]. Based on the Theory of Planned Behavior (TPB) and the Normative Activation Model (NAM), this paper constructs a research model of the factors influencing the willingness of the digital economy to green production in the equipment manufacturing industry from the aspects of rationality and morality. The failure of hypothesis H13 may be attributed to the fact that, despite managers possessing the requisite knowledge, skills, and abilities to address environmental issues, limitations stemming from the enterprise's developmental stage, economic capacity, and employee skill sets could render managers powerless. Similarly, the H14 hypothesis may have faltered due to the ineffectiveness of government-formulated preferential policies in achieving cost reduction and increased efficiency for many enterprises. Alternatively, it could be that the public's demands for green production are not substantial enough to motivate unwilling enterprises.

The findings reveal that the digital economy exerts a positive influence on personal norms, responsibility attribution, consequence awareness in NAM, attitudes, cost savings, self-efficacy, and social pressure in NAM. Consequently, there is a need for enterprises to enhance their digital economy capabilities.

Moreover, the results indicate that personal norms, responsibility attribution, and consequence awareness positively impact green production willingness. Therefore, enterprises should establish corporate personal norms and elevate their awareness of responsibility attribution and consequences.

Furthermore, attitudes and cost savings exhibit a positive correlation with green production intentions. To foster green production intentions, there is a necessity to intensify environmental protection advocacy, fortify green production policies, and positively shape enterprises' attitudes towards green production. The promotion of the deep integration of the digital economy and the equipment manufacturing industry emerges as a strategic approach to achieving cost savings.

B. Theoretical Contributions

This paper enriches research in the field of the digital economy. It scientifically and systematically identifies the influencing factors of the digital economy on the green production willingness of the logistics equipment manufacturing industry, constructing theoretical models based on the Theory of Planned Behavior (TPB) and normative activation model (NAM), thereby contributing to the advancement of research in the digital economy.

C. Practical Contributions

After reviewing a large number of literatures, it is found that there are many researches on green production in the manufacturing industry, but there is a lack of research on the digital economy; and there are few researches on the green production of the manufacturing industry in the research on the digital economy.

Therefore, in order to promote green production in the manufacturing industry through the digital economy, it is necessary to explore the factors that affect the willingness of the manufacturing industry to produce green. By exploring these factors, this paper puts forward relevant suggestions for enterprises to promote green production in the manufacturing industry.

D. Limitations and Future Directions

Firstly, the generalizability of the findings in this paper is limited as it solely represents the situation within China's equipment manufacturing industry. The applicability to equipment manufacturing industries in other countries may be restricted. Secondly, there are shortcomings in the scale design and selection of influencing factors. Although seven influencing factors have been identified based on extensive literature review, the inherent complexity of green production in the equipment manufacturing industry suggests the presence of numerous intricate factors that may introduce subjectivity into the research.

Lastly, the lack of maturity in companies' understanding of the digital economy, coupled with the imperfect state of China's green production system, has led to a relatively small sample size in this study.

Addressing these limitations, future research endeavors should focus on increasing the sample size. Employing a combination of quantitative and qualitative methods, such as questionnaires and interviews, can enhance data collection. Deepening the research at the grassroots level within enterprises and conducting more comprehensive investigations into green production will contribute to a more nuanced understanding. Furthermore, there is a need for in-depth discussions on the influencing factors of the digital economy and green production in the equipment manufacturing industry. The theoretical model assumptions should be expanded, and a mix of qualitative and quantitative methods should be employed to ensure the scientific rigor of the research results.

Acknowledgement

This work was supported by: (1) The Science and Technology Development Project of Henan Province in 2024 (Soft Science Research) (grant number: 242400410005); (2) The R&D and Promotion Key Program of Anyang in 2020 (grant number: 2020–256) and (3) The Development Program for University Key Teacher of Henan Province (grant number: 2020GGJS233).

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