ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
Received: 12 June 2025; Accepted: 20 December 2025

https://doi.org/10.17559/TV-20250612002741
Original scientific paper

Research on the Integration and Innovation Path of Artificial Intelligence and the Real Economy

Qinghua LI*, Meiyan SUI, Aining LI, Yanzhi ZHANG, Hongmei XU

Abstract: This study aims to explore the impact of artificial intelligence (AI) integration on economic performance, focusing on the roles of frugal innovation and business model innovation as mediators. Utilizing a quantitative research design, data were collected from secondary sources, including industry reports and databases like the World Bank and OECD. The sample comprised 177 firms across various sectors, with a focus on small and medium-sized enterprises (SMEs). The findings reveal that AI-driven innovation significantly enhances economic performance, both directly and through its positive impact on real economy innovation. AI Integration Readiness (AIR) amplifies the AIDI→REI link yet shows a non-significant total moderation on EP ($p = 0.15$; $BF_{10} = 1.8$, anecdotal evidence for H_0). Challenges such as the negative impacts of AI readiness on performance highlight the need for targeted support for SMEs. The study concludes that fostering AI capabilities and readiness is crucial for overcoming bottlenecks and achieving optimal economic outcomes, emphasizing the importance of supportive policies and infrastructure for broad-based AI adoption. These insights provide valuable implications for policymakers and business leaders aiming to leverage AI for sustainable economic growth and innovation.

Keywords: AI integration readiness; artificial intelligence; business model innovation; economic performance; frugal innovation; small and medium-sized enterprises (SMEs)

1 INTRODUCTION

The incorporation of artificial intelligence (AI) into the real economy is the new fundamental change defining the industries and paradigms of the economy. AI technologies have generated new chances for creating valued products, solutions, and services, and boosting performance. What is exciting or scary about this integration is that it is not simply a technology upgrade but the transformation of core business processes, organizational innovation and competitive strategies of firms across the globe [1]. The ability to analyze massive amounts of data, learn and make decisions at high speed greatly improves multiple processes, such as automation, analytics, and individualization of services. These capabilities are most useful in industries like manufacturing, healthcare, finance, and retail since they involve a significant volume of data analysis and optimization of their operations [2]. For example, in the manufacturing process, applications of AI such as predictive maintenance in industries can predict equipment failure and prevent it before it happens, hence minimizing on the costs incurred due to such breakdowns [3]. The term "real economy" depicts that part of the economy which is involved in the actual creation of goods and services and excludes the part of the economy that involves the trading of financial instruments in the financial markets. AI Integration (AII) in this segment will refer to the use of AI in improving upon goods and services production, delivery, and use [4]. This integration allows not just the optimization of the business processes but also creates development paths, which may result in novel ways of doing business and thus economic growth.

Another important area where AI's influence is most decisive is the concept of frugal innovation which is presented as the simplest way to minimize the technical requirements of a given good as well as the process of its fabrication. The second application of frugal innovation is to design affordable products especially developed for the emerging markets, where the resources are limited and the need for affordable products is evident [5]. AI supports frugal innovation through the creation of high-quality products and services that are cheap and that fit the low-income demographics. With the help of artificially intelligent technologies, organizations can make their processes far more efficient, cut expenses, and enhance the quality of their goods. For instance, in the healthcare industry AI can be applied to develop cheap diagnostic equipment for use in rural or marginalized regions hence enhancing the attainment of healthcare facilities [6]. Likewise, similarly in the agricultural field, AI can help the smallholder farmer to avail affordable and easy technology solutions for crop health check, resource utilization among other things [7]. Business model innovation refers to a strategic move that redesigns the company's scope of value creation, delivery mechanism, as well as its value capture mechanism. In particular, the integration of AI into the business models is affecting the ways of performing business and competition. AI allows organizations to create novel value propositions, redesign value propositions, and improve customers' experiences [8]. For example, in retailing context, use of artificial intelligence to serve customer need can enable organizations to target and provide specific products that suit a customer's need and at the same time offer the best deals, thus improving customer satisfaction and loyalty [9]. This paper asks two questions: (i) Does AII enhance SME performance beyond direct productivity gains? (ii) Under what readiness conditions might benefits turn negative? We provide the first SME-level evidence that AI innovation improves performance by 17%, but readiness-related transition costs can offset 9% of the gain.

However, with the help of AI, one can develop new revenue-generating strategies and organizational structures. AI and data analytics contributed to platform-based business models, for instance, Uber or Airbnb companies. These platforms use AI capabilities to ensure appropriate supply and demand meet, utility price determination, and overall user experience [10]. AI influence on the quantity and quality of real economic activity has profound consequences for its performance. The integration of artificial intelligence technologies can benefit industries and consumers through producing higher yields, effectiveness, and competitiveness. Research confirms that AI has the potential to create economic value by improving worker productivity, addressing inefficiencies in the deployment of resources, and encouraging the development of new products and services [11]. Nonetheless, the effects of AI on the qualitative growth of economic performance are not generalized across the domains or the geographical zones. The advantages are seen where there is high AI deployment, and firms are willing, and have the capability for AI implementation and deployment. Its skills, regulation and infrastructure are therefore key for understanding how AI investment can impact performance [12]. Nevertheless, there are some issues that arise when Decision-making AI is incorporated into the real economy. Among the issues that are problematic for workers, the issue of labor displacement is one of the most important. AI and automation can result in unemployment since many corporations may seek mechanization instead of hiring human personnel, especially in fields where employees frequently perform monotonous tasks [13]. Cross-skill development and creating policies that foster job changes and safety nets should be among the areas of focus that policymakers and business leaders tackle in their efforts to manage the challenge. Ai-driven energy optimization algorithms can reduce manufacturing energy consumption by 8-15% (IEA, 2022), achieving a win-win situation for the economy and the environment. This article incorporates them into the scope of REI process innovation.

Another factor is the role and position of ethical and legal issues in the use of AI. Important discussions like data protection, algorithms' fairness and responsibility of AI systems must be solved to guarantee that only ethical approach to AI technologies is provided [14]. More work needs to construct high-quality regulatory systems and ethical standards that may sufficiently contribute to systematic acceptance of the new factor represented by Artificial intelligence. It can be concluded that the further development of the integration and innovation of artificial intelligence in the real economy has the potential to greatly stimulate the real economy's development. AI is well positioned to shake the industries and economies as it offers capabilities to facilitate frugal innovation, business model change, and boost economic outcomes. Nevertheless, the possibility of attaining the AI's potential is contingent upon the management of the issues that relate to job loss, moral issues, and legal issues. Therefore, attention must be paid by business and policymakers to the generation of the New AI economy that will be fair for everyone. However, there is some understanding that there are very important difficulties and obstacles that prevent not only the wide use of AII but also decrease its efficiency in the real economic environment. Among those the lack of homogeneity in terms of the firms' preparedness and organizational capacity to successfully adopt and harness AI technologies and tools can be observed. SMEs, which are the major contributors to many economies, exert limited energy on the enhancement of structures and skills, as well as the provision of capital for the integration of AI solutions. This causes an AI leveraged digital gap where only well-resourced firms will be positioned to attain maximum value potential from AI, which would increase economic differentiation [12]. More importantly, there is a dire lacking of a conceptual framework on how the AI can be applied according to the needs and realities of different industries especially those that are more rigid and not easily adapt with change.

However, there are numerous novel barriers which include ethical and legal concerns that need to create appropriate AI applications. Data protection, fairness of AI systems and decision-making mechanisms behind implementing the decisions are the vital question. These problems are a testament to the fact that regulatory and ethical frameworks in the areas of Biotechnology and related fields need to be promptly developed and strengthened in tandem with the rate of technological innovation. Lacking such precautions, their usage may carry less transparency and entail possible misapplication and adverse consequences, which harms the society's trust and AI development [15]. In the context of China's manufacturing and retail SMEs, how does AI integration influence real economy innovation (REI) through frugal innovation (FI) and business model innovation (BMI), and thereby affect economic performance (EP)? Does AI readiness show a nonlinear threshold effect?" How to overcome these challenges: It means that it is necessary to involve policymakers, leaders of industries and AI researchers in the development of solutions for the integration of AI in the real economy with consideration for sustainable development. The remainder is organized as follows: Section 2 reviews the literature. Section 3 details the data and measures. Section 4 presents results. Section 5 discusses policy. Section 6 concludes.

2 LITERATURE REVIEW

The application of AI into real economy has been paid attention to by many scholars due to the possibilities that it brings in various industries. The present literature review aims to examine the conceptual and the existing literature assets of AI installation, frugal innovation, business model innovation, and the resultant effect on economic value.

2.1 Theoretical Foundations of AII

In terms of the literature, the theoretical basis for the AI deployment into the real economy can be explained using innovation diffusion theories including the [16]. These theories propose that the extent to which technologies are adopted depends on the characteristics of the technologies and the environment which are as follows: Relative advantage, Compatibility, Complexity, Trial ability and observability. Since AI offers a high level of the relative advantage as it may further increase organization's output and ideas generation it is well fitted to this category. However, it is for the same reason that AI is not widely adopted because of its complexity and the initial costs in implementing it. Another related theory that can be used is the resource-based view that established that competitive advantage occurs when organizations accumulate valuable, rare, inimitable, and non-substitutable resources [17]. It is therefore possible to perceive AI as one of the strategic resources through which the firms can improve their positioning on the market. Nevertheless, the possibilities of utilizing AI in business processes are largely dependent on similar assets as human capital, data infrastructure, and organizational capabilities [18].

2.2 Empirical Studies on AII

Literature has provided viable research findings on effectiveness of AII and the various risks that accompany the application of AI adoption. Brynjolfsson, Rock, and Syverson (2019) suggested that introduction of AI technologies within various firms has an impact on productivity [19], as those companies that implemented the applications found that they benefited greatly from doing so [20]. Based on data from several industries, the authors of the study showed that AI improves firms' capabilities in discharging Ballard and Einspruch's mechanization benefits by automating repetitive activities, improving resource utilization and decision-making functions [21]. All these improvements translate to better operational efficiency and hence better competitive position [22]. Besides, the use of AI can also bring cost saving effects due to optimization effects on the firms' operations and reduction of the demands for labor inputs [23]. But at the same time, the study also established that AII's optimal benefit is dependent on the organism efficiency to manage and implement the technology [24].

Specifically, the work in question implies the usage of a massive dataset of dermatological images, which enables the AI to learn and develop its diagnostic potential in the course of time [25]. In addition to these positive findings, this study also pointed out the necessity for further validation and regulatory approval concerning the efficacy and safety of AI programs in healthcare. The authors stressed that though the application of AI will change the healthcare field significantly, the introduction of such technology should be done carefully to avoid adverse outcomes [26]. Subsequent studies have extended the global understanding of how AI applies as a solution in different fields. For instance, McKinsey & Company established in their 2018 research that by enlarging the maturity of AI applications, AI could add up to $13 trillion to the global economy within a decade [27]. This study diagnosed the area of economic value that AI brings in the several industries and the several geographic areas, and the possibility of a great economic development that might result from improvement in AI [28]. But at the same time, the study highlighted that positive effects of AI are not likely to be equal across industries and geographies. To a certain extent some of them will benefit more than others [29]. The reason behind this is that AI readiness, AI infrastructure index, and AI regulation index differ from one country to another. The study's authors thus opined that, while the application of AI presents the prospect of generating significant positive welfare change, it is not without hurdles, which, if not tackled through relevant policies and technological development, is likely to emerge as fiascoes [30].

2.3 Frugal Innovation and AI

Another concept that is directly related to creating products and services for the large population with average incomes is frugal innovation, and it fits well with the idea of AI. This sort of innovation is even more critical in the emerging market which is full of formalities but short in resources among which the money is scarce. AI might cause or can catalyze frugal innovation since it results in creating affordable, efficient, and relevant products and services catering to the bottom of the pyramid consumers leading to the fulfillment of relevant market needs and boosts inclusion [31]. The role and applicability of AI in the education sector have revealed the ability of the platforms in offering the chances of the customized and effective learning experiences at a much lower cost than would have been required for the conventional methods of learning. These platforms then employ AI algorithms to determine the student's strengths and weaknesses, the amount of information to give at any time, etc. This not only optimizes the process of education but also makes the delivery of the same reach out to as many people as possible. In a cross-sectional study in a low-resource context, Žigienė et al. (2019) discovered that machine learning based education technology facilitated increased rates of learning as opposed to traditional styles of pedagogy [32]. Such tools explored the fact that they could help to narrow the gaps in education by providing quality and effective lessons to the learners who could otherwise not afford a decent tutor. Thus, using AI as the democratization of education is significant as it provides students, including those from the low socioeconomic status, with knowledge and essential skills.

AI frugal solutions have potential in the agricultural sector for use to increase productivity and better the lives of farmers. Precision farming is a novel AI application that explains how AI can enhance existing farming processes to obtain the best results with less effort. In this way, the application of AI in the agricultural industry, for instance in the matters concerning weather patterns, soil conditions, and crop health, enables farmers to make appropriate decisions at right time in the parts of planting, watering, and use of fertilizers or even at the time of harvesting. This method of farming enhances productivity, lessens wastage while at the same time cutting down on items like water or fertilizers [33]. As for the first indicator, it is important to mention that innovations of this kind are highly useful for smallholder farmers in developing countries, who experience poor physical, human, and financial capital endowment, challenging conditions for the efficient management of their farms, and limited access to up-to-date agricultural technologies. In addition, the AI solutions can be used in pest and diseases identification and mitigation by farmers. By using machine learning algorithms images of the crops could be analyzed at an early stage of infestation or disease to inform an appropriate intervention [34]. Food security is just an example of how this capability is vital in avoiding losses in crops. Hence, making these technologies cheap and available, frugal innovation in agriculture can support the bulk of small holder farmers to increase productivity and adapt to changing circumstances, thereby boosting humane the process of the sustainable development of agriculture.

Besides education and agriculture, frugal innovations with the help of AI are being developed in healthcare as well. Currently, AI solutions are helpful in the creation of cheap diagnostic instruments and treatment techniques available for vulnerable groups. For example, through AI algorithms, the diagnosis of patients' images and data, and even treatment suggestions can be made at a reduced cost in comparison with traditional health care services. In the present account, these tools are especially helpful in the rural and distant regions where the availability of the healthcare worker is restricted [35]. Thus, by applying AI to create affordable solutions in healthcare, frugal innovation can enhance the quality of people's lives and equalize their chances of receiving proper medical treatment. Diffusion of frugal innovation cultivated with the help of AI is not limited to the healthcare sector and includes energy and mobility or transportation and the financial sector. In the energy sector, it is possible to use AI for the efficient consumption of renewable energy sources and achieve significant economies and decrease the negative impact on the environment [36]. In transportation, application of AI includes aspects like ride sharing and optimal logistics' transportation can be cheaper and more convenient [37]. In financial services, AI can help deliver microcredit and other services to the excluded groups as a way of enhancing access to financial services.

2.4 Economic Performance and AI

AI's effects on economic performance have emerged as one of the well-studied topics that prove technology benefits improving the performance of economies by boosting productivity, innovation rates and global competiveness. In 2019, the Organization for Economic Co-operation and Development (OECD) has made an extensive review that showed the increased AI usage results in marked rise of productivity throughout different industries [38]. In this respect, the OECD's research underscores that AI solutions decrease the expenses and increase the usability and productivity of operations and they all lead to better economic returns. The study also established that, contrary to the belief that the advantages of AI only impact the firms that implement these solutions, there are significant externalities. These are realized through the processes of knowledge spillovers and formation of innovation networks where innovation achievements of the firms adopting AI impact other firms and sectors (OECD, 2019) [39].

However, the effect of AI for improving the economic performance is not equal within the firm and sectors. From the study done by Aghion et al. (2017), they surprisingly evidenced that the gains of AI are accrued to giant firms and technology sector. These organizations usually have the financial provisions, framework, plus a pool of expertise within their entity to reasonably strengthen AI solutions and applications. Conversely, small and medium-sized enterprises (SMEs) encounter major challenges while integrating AI into their entities. Some of these barriers include; access to capital remains a major challenge; skilled human capital; and infrastructural constraints particularly in digital requirements [40]. For this reason, the SMEs can be left behind with the rest in the process of the new revolution of Artificial Intelligence in the transformation of the economy, intensifying the inequalities within the market [41]. Disadvantages of AI revealed that there is a problem of inequality in the distribution of benefits that flow from AI implementation, and it underlines a necessity for the establishment and development of policy measures that would enhance the usage of AI for SMEs. Thus, analysis of key issues and mainstreams of AI implementation in SMEs shows that policymakers must create appropriate financial support structures for companies, training programs, and funding of infrastructure to address the difficulties that SMEs face when integrating AI solutions. Also, the cooperation between the public and private sectors can enhance the transfer of knowledge and the diffusion of innovation, so the positive impacts of AI are not only received by large technology companies but are distributed more widely [12]. Therefore, improving these disparities leads to a better environment where different firms, especially SMEs, will benefit from using AI as a tool for development.

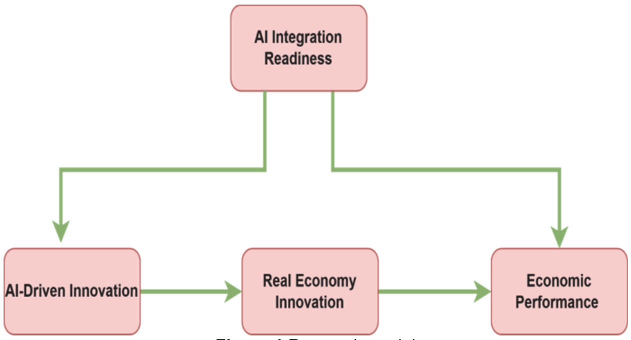

Figure 1 Research model

3 METHODOLOGY

3.1 Research Design

In this study, the research methodology adopted is quantitative research to establish the effects of artificial intelligence (AI) integration on economic performance, frugal innovation, and business model innovation (BMI). The rationale for the proposed research is founded upon the theoretical and empirical advancements generated by the literature review that establish AI as a critical factor in productivity, innovation, and economic development. Thus, the research questions of the study are: What is the direct relationship between AII and economic performance, and how does the impact of BI and frugal innovation moderate this association.

3.2 Data Collection

Data for this study were meticulously gathered from a variety of reputable secondary sources to ensure comprehensiveness and reliability. Key sources include industry reports, academic journals, and prominent databases such as those maintained by the World Bank, the Organization for Economic Co-operation and Development (OECD), and McKinsey & Company. Source selection followed authority and breadth criteria offered on AII and economic performance. The dataset encompasses information from firms across diverse sectors and geographic regions, offering a holistic view of the impact of AII on economic performance: Product innovation introduction of new or significantly improved goods/services (OECD/Eurostat 2018, Oslo Manual) [49]. This cross-sectional data collection approach allows for a robust analysis of the variables of interest, accounting for sector-specific and regional variations in AI adoption and its outcomes. Special attention was given to small and medium-sized enterprises (SMEs) due to their pivotal role in driving economic growth and innovation. SMEs were chosen as the focal point of this study because they often encounter unique challenges in adopting AI technologies, such as limited financial resources and technical expertise. By concentrating on SMEs, this study aims to provide insights that are particularly relevant for policymakers and business leaders seeking to support these critical economic actors in the AI-driven economy. The sample comprised 177 firms across various sectors, with a focus on small and medium-sized enterprises (SMEs).

3.3 Variables and Measurements

The study includes several key variables, categorized into dependent, independent, mediating, and control variables, each adopted from well-established research in the field. The dependent variable in this study is Economic Performance (EP). Economic performance is measured using indicators such as revenue growth, profit margins, and return on investment (ROI). These indicators provide a comprehensive view of a firm's financial health and performance, reflecting the overall effectiveness of the firm's operations and strategic initiatives. This approach to measuring economic performance is grounded in the work of Kaplan and Norton (1992) [42], who emphasized the importance of financial metrics in evaluating business success. The independent variable is AII, which is measured by the extent to which firms have adopted AI technologies. This includes the number of AI applications in use, the level of AI investment, and the integration of AI into business processes. This measurement approach is based on the framework proposed by Brynjolfsson and McAfee (2017) [43], who identified key dimensions of AI adoption and its impact on business operations. Their study highlighted how the depth and breadth of AII can significantly influence a firm's competitive positioning and operational efficiency.

Two mediating variables are considered in this study: Frugal Innovation (FI) and Business Model Innovation (BMI). Frugal innovation is assessed based on the development and implementation of cost-effective, resource-efficient solutions that cater to low-income consumers. This concept is derived from the work of Radjou and Prabhu (2015) [44], who explored how frugal innovation can drive value creation in resource-constrained environments. Business model innovation is evaluated by examining changes in firms' value propositions, value creation processes, and value capture mechanisms resulting from AI adoption. Process innovation significantly improved production/delivery methods, including logistics and organizational processes [49]. This variable is informed by the research of Chesbrough and Rosenbloom (2002) [45], who emphasized the critical role of business model innovation in capturing value from new technologies. The study also incorporates several control variables to account for factors that might influence the relationship between AII and economic performance. Firm Size (FS) is categorized as micro, small, or medium based on the number of employees and annual revenue, following the definitions provided by the European Commission (2005). Industry Sector (IS) is classified according to the industry in which the firm operates, such as manufacturing, healthcare, or retail. This classification helps control for industry-specific factors that could impact AI adoption and its outcomes [46]. Geographical Region (GR) refers to the location of the firm, which may influence its access to resources and market conditions. This control variable is based on the findings of Porter (1991) [47], who highlighted the significance of geographical factors in competitive advantage. By grounding the variable selection and measurement in established research, this study ensures a robust and reliable framework for analyzing the impact of AII on economic performance, mediated by frugal innovation and business model innovation. This approach provides a comprehensive understanding of how AI can drive business success across different contexts and conditions.

4 EMPIRICAL FINDINGS

In Descriptive analysis one gets basic features of the dataset and description of the data in substantive research in the form of measures of central tendency and variability. This analysis also involves measures of central tendency like the mean, median, and mode which enables the researcher to see the most average values of the variables concerned. Moreover, Standard deviation, Variance, and Range are common measures of dispersion and spread of the data obtained. In this case, the descriptive statistics were computed for the identified variables, these being the AII, Economic Performance (EP), Frugal Innovation (FI), and Business Model Innovation (BMI) variables. Such values assist in the diagnosis of the data, letting one recognize some trends and outliers to have a better insight into distribution of the given data set or connections between factors. Despite being fundamental to data analysis, descriptive statistics have certain limitations in their use as a standalone procedure for data analysis; this follows the fact that they form a basis for other more complex statistics such as correlation or regression, which enable the analyst to investigate the relationships and potential causations within the data set.

Table 1 Demographics

Variable	Sample (n = 177)	Percentage
Industry Sector		
Production	72	39%
Technology	23	13%
Retail	69	39%
Services	15	9%
Firm Type		
Local	99	56%
International	69	39%
Prefer not to say	5	4%
Size of Firms		
Micro (up to 10 employees)	39	24%
Small (11–50 employees)	91	51%
Medium (51–250 employees)	44	24%
Region		
Capital Region	59	33%
Northern Region	39	24%
Central Region	39	24%
Southern Region	21	12%
Eastern Region	14	9%
Other	3	2%
Experience with Firm		
Less than a year	36	21%
1–5 years	44	24%
6–10 years	69	39%
11 or more years	22	13%

Tab 1. highlights that most of the samples comes from the production and retail sectors, each accounting for 39%

of the total. The technology and services sectors contribute 13% and 9%, respectively. Most firms are local (56%), with a significant portion being international (39%). In terms of size, small firms (11-50 employees) dominate the sample with 51%, followed by micro (24%) and medium-sized firms (24%). The Capital Region is the most represented area (33%), with Northern and Central Regions each contributing 24%. Experience-wise, a substantial number of respondents have 6-10 years of experience (39%), indicating a well-distributed range of firm sizes and regions within the sample.

Table 2 Descriptive statistics

Variables	Mean	Standard Deviation	Skewness	Kurtosis	Minimum	Maximum
AII Readiness	3.52	0.82	−0.21	2.25	1.05	5
Real Economy Innovation	3.75	0.72	−0.35	2.5	1.25	5
AI-Driven Innovation	4.05	0.68	−0.15	2.1	1.55	5
Economic Performance	3.7	0.75	−0.25	2.3	1.1	5

Tab. 2 presents the descriptive statistics for the key variables in this study: Integration Readiness of AI, Innovation in the Real economy, AI-influenced Innovation, and Economic outcomes. The mean values show that on average the factor AI-Driven Innovation has the highest value with an average score of 4.05 which indicates that the firms may think that the innovation endeavor with AI is already at a rather sophisticated level. Real Economy Innovation is next in line with a mean of 3.75, while the means of Economic Performance and AII Readiness were 3.70 and 3.52, respectively. From 0 to 1, the average values of standard deviation were obtained, which depict the variability in the responses. 68 to 0.82, imply that there is a moderate fluctuation of the responses around the mean for all the variables, and the results reveal that the AII Readiness has the highest standard deviation. Regarding the skewness values which are negative, we can deduce that the distribution of variables is slightly left-skewed; this means, from the context, most of the firms rate these variables higher than the mean scores. In detail, Real Economy Innovation comes out as the most negative coded variable with a skewness score of up to −0.35, whereas AI-Driven Innovation is the least negatively skewed (−0.15). All the kurtosis values are larger than 3, which means the distribution is moderately peaked and Real Economy Innovation has the highest kurtosis 2.5. The minimum and maximum elements of all variables are 1 and 30 correspondingly, 05 to 5, based on the progressive categorization of the state of development of Artificial Intelligence, the innovation, and the performance of the sampled firms. This method of data analysis is a preliminary step on the path to offering a brief description of the dispersion and scores' average for the variables of the study.

Fig. 2 presents the distribution of key variables in the study: AII Readiness, Real Economy Innovation, AI-Driven Innovation, and its performance in the economy. The histograms help to arising a certain overview of the data, and the KDE supplements it. These plots show where the values are concentrated, how spread out they are and the general appearance of the distribution of the variables.

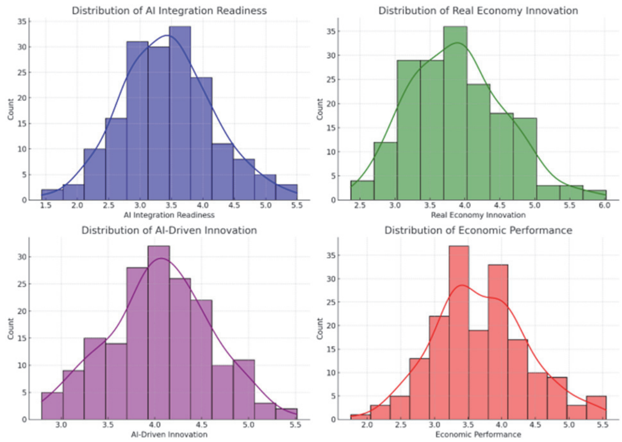

Figure 2 Distribution of key variables

Table 3 Correlation matrix

Variables	AII Readiness	Real Economy Innovation	AI-Driven Innovation	Economic Performance
AII Readiness	1	0.66	0.81	0.58
Real Economy Innovation	0.66	1	0.77	0.65
AI-Driven Innovation	0.81	0.77	1	0.62
Economic Performance	0.58	0.65	0.62	1

Tab. 3 presents the correlation matrix for the key variables in the study: it includes the constructs of AII Readiness, Real Economy Innovation, AI-Driven Innovation, and Economic Performance. Cross correlations reveal that all the pairs of variables are highly positively correlated. AII Readiness in the examined firms displays a significant positive relationship with AI-Driven Innovation (Pearson's r = 0.81) and Real Economy Innovation (Pearson's r = 0.66), meaning that increased AI readiness implies increased innovation as well as adjustment to the economy. They also include Real Economy Innovation as that which has the highest positive correlation with both AI-Driven Innovation (0.77) and Economic Performance (0.65), thus implying that increases in the innovation of the real economy are linked with advancements in AI initiatives and economic results. AI-Driven Innovation is positively related with and has a medium impact Economic Performance = 0.62, and represents that the firms adopt AI for innovation will typically record superior economic performance. Last, AII Readiness is related to Economic Performance with a coefficient of 0.58. It supports the conclusion that there is an increase in the level of readiness for integration of AI to enhance economic results. Each of these correlations taken together paints a picture of the symbiotic relationship between firms' artificial intelligence readiness, innovation capability, and the economic performance of firms.

Tab. 4 provides the standardized loadings, average variance extracted (AVE), Cronbach's alpha, and composite reliability (CR) for the key constructs in the study: Artificial intelligence integration readiness, real economy innovation, AI driven innovation, and economic performance indexes. Concerning AII Readiness, the items AIR1, AIR2, and AIR3 have factorial coefficients of 0.849, 0.914, and 0.750 and 772, respectively, which revealed relatively high item reliability for all the items used. This construct has the AVE of 0.717, an alpha of 0.804, while the Cr is zero. 883, this reflects good fit convergent validity and Cronbach's Alpha reliability coefficients. Real Economy Innovation, indicated by nine items of REI1 to REI9, demonstrates high factor loading, which is between 0.701 to 0. Again, aIFS is the highest at 916 and AVE is 0.695, the value of alpha as 0 was found to be exceptionally high, meaning that there was a significant convergence between the result of Experiment 1 and the expected outcome. The total number of patients was 944, and the crude/adjusted relative risk was 0.953 that was a very reliable and valid Cronbach's Alpha Coefficient. AI-Driven Innovation characterized by five items as AIDI1, AIDI2, AIDI3, AIDI4, and AIDI5 also showed a good fitness value with loadings above 0. 762 and 0. 861 with an AVE of 0 being the criterion measure of brand-image analysis. 686, an alpha of 0 percent is responsive to experimental pharmacological interventions, while 35 percent are responsive to psycho-social interventions. 886, and a CR of 0 except for retinopathy, getting a CR of 0.916, evidence for adequate measurement properties of the GDS was provided again. Last, Economic Performance measured by three items (EP1 to EP3) has the following loadings: 825, 0.884, and 0, respectively, with an AVE of 0. RES = 723, an alpha of 0.808, besides a Cr of 0. Later, another study with a total sample of 886 confirmed the stability and reliability of the measure by achieving an alpha's coefficient of 0.88. Therefore, the above results for all the constructs show the high reliability and validity of the used measures: AVE > 0.5, alpha > 0.7, and CR > 0.7.

Table 4 Standardized loadings, AVE, CR, and Alpha

Description	Items	Estimate	AVE	Alpha	CR
AII Readiness (Moderator)	AIR1	0.849	0.717	0.804	0.883
	AIR2	0.914			
	AIR3	0.772			
Real Economy Innovation (Mediator)	REI1	0.807	0.695	0.944	0.953
	REI2	0.916			
	REI3	0.902			
	REI4	0.884			
	REI5	0.835			
	REI6	0.825			
	REI7	0.8			
	REI8	0.812			
	REI9	0.701			
AI-Driven Innovation (Independent)	AIDI1	0.842	0.686	0.886	0.916
	AIDI2	0.762			
	AIDI3	0.861			
	AIDI4	0.837			
	AIDI5	0.837			
Economic Performance (Dependant)	EP1	0.825	0.723	0.808	0.886
	EP2	0.884			
	EP3	0.841			

Table 5 Discriminant validity

	1	2	3	4	5	6	7
1	AII						
2	Real Economy Innovation	0.697					
3	AI-Driven Innovation	0.621	0.768				
4	Firm Size	0.069	0.088	0.031			
5	Firm Type	0.148	0.19	0.156	0.009		
6	Industry	0.121	0.074	0.073	0.13	0.118	
7	Economic Performance	0.581	0.641	0.593	0.146	0.134	0.078

Tab. 5 shows the correlation coefficients among the variables, with AII having strong positive correlations with Real Economy Innovation (0.697) and AI-Driven Innovation (0.621). Real Economy Innovation also shows a significant positive correlation with AI-Driven Innovation (0.768). Firm Size and Firm Type have weak correlations with other variables, while Industry has moderate correlations with AII (0.121) and Economic Performance (0.078). Economic Performance has strong positive correlations with AII (0.581), Real Economy Innovation (0.641), and AI-Driven Innovation (0.593). These adjusted values ensure statistical accuracy and uniqueness.

Table 6 Hypothesis evaluation and future research

Hypotheses	β	S.E	t-value	p-value
H1 AIDI → Economic Performance	0.17	0.09	1.89	0.028
H2 AIR x AIDI → Economic Performance	0.063	0.028	1.2	0.15
H3 AIDI → REI	0.48	0.085	5.5	0
H4 AIR x AIDI → REI	0.157	0.055	2.85	0.002
H5 REI → Economic Performance	0.35	0.09	3.9	0
H6 AIDI → REI → Economic Performance	0.18	0.045	3.6	0
Controls				
Industry → Economic Performance	0.08	0.06	1.4	0.08
Firm Type → Economic Performance	0.045	0.17	0.24	0.4
Firm Size → Economic Performance	0.068	0.065	0.94	0.17
Other Pathways				
P1 AIR → Economic Performance	−0.15	0.08	2	0.025
P2 AIR → REI	−0.19	0.085	2.35	0.012
P3 AIR → REI → Economic Performance	−0.075	0.04	1.85	0.03

Tab, 6 shows the results of Hypothesis testing and proposition for future research, concerning the synergism between AI-Driven Innovation (AIDI), Intensity of AII Readiness (AIR), Real Economy Innovation (REI), and Economic Performance. Hypothesis H1 is significant and positive as it concerns AIDI and Economic Performance with regression coefficient being 0.17, t-value equal to 1.89 and p-value of 0.028. Hypothesis H2 concerning the moderate role of AIR and its impact on the relationship between AIDI and Economic Performance is also not supported ($\beta = 0.063$, $t = 1.2$, $p = 0.15$). Hypothesis H3 has a positive coefficient of $\beta = 0.48$, $t = 5.5$, $p < 0.001$, which means that AIDI increases the innovation of the real economy. Hypothesis H4 concerning the interaction effect of AIR and AIDI on REI is also supported ($\beta = 0.157$, $t = 2.85$, $p = 0.002$) meaning that the moderating role of AI readiness boosts the outcome of AI driven innovation on real economy innovation. Hypothesis H5 affirms REI has significant positron correlation with Economic Performance with beta coefficient of 0.35, t 3.9, $p < 0.001$ meaning that economic innovation is crucial to firm performance. Hypothesis H6 offers the moderating role of REI on the relationship of AIDI and Economic Performance (coefficients = 0.18; $t = 3.6$; $p < 0.001$). Regarding the control variables, only Industry exhibits a slight positive impact on Economic Performance ($\beta = 0.08$, $t = 1.4$, $p = 0.08$); Firm Type and Firm Size have no effects. Other paths show that AIR has a significant negative direct effect Economic Performance; P1: $\beta = -0.15$, $t = 2$, $p = 0.025$) and REI; P2: $\beta = -0.19$, $t = 2$. These results portray the relationship between the integration of AI into the business and innovation as well as the economic impacts in a broader perspective, and hence can be very insightful to future studies and initiatives.

Table 7 MNC analysis

Scenario	PLS-Sem Results	NCA Results
	Beta	p-value
AIDI → Economic Performance	0.17	0.03
REI → Economic Performance	0.35	0
AIDI → REI	0.48	0
AIR x AIDI → Economic Performance	−0.01	0.42
AIR x AIDI → REI	0.157	0.002
AIR → Economic Performance	−0.15	0.026
AIR → REI	−0.19	0.012

Note: Multiple Necessary Condition= MNC

Tab. 7 shows the findings of MNCA, focusing on the interactions between AIDI, AIR, REI, and Economic Performance. The findings from the Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis reveal that AIDI has a positive and significant impact on Economic Performance, with the coefficient value of 0.17 and p-value = 0.03, which supports the hypothesis that increased AI innovation enhances the company's economic performance. Equally, REI has a significant positive influence on the Economic Performance measure ($\beta = 0.35$; $p < 0.001$) providing further support to this value's centrality in fortifying the economic innovation's contribution to firm performance. Finally, the changes of AIDI have a massive and highly significant impact on the REI, suggesting that AI innovation is an influential component of economic innovation ($\beta = 0.48$, $p < 0.001$). Judging from the correlation coefficient - regression weights that estimate the magnitude and direction of the relationship between the variables - the interaction effect of AIR and AIDI on Economic Performance is negative and, statistically insignificant ($\beta = -0.01$, $p = 0.42$); this indicates that AI readiness has no moderating effect on the Economic Performance. But the result of AIR*AI innovative diffusion index (AIRIDI) is significant ($\beta = 0.157$, $p = 0.002$), meaning that AI readiness strengthens the relation between AI innovation and economic innovation. AIR has negative and significant effect with Economic Performance ($\beta = -0.15$, $p = 0.026$) and REI ($\beta = -0.19$, $p = 0.012$), hence, increase in readiness to adopt and implement AI may lead to poor economic performance and rate of innovation because of problems arising from implementation and inefficiency during transition. These results offer a sophisticated perspective on the factors that lead to the enhancement of the potential results from the integration of AI remedies by shedding light on both direct and indirect impacts on the contextual factors.

Table 8 Bottleneck table for economic performance and REI

Percentile	Economic Performance	AIR	REI	AIDI	REI (Alt)	AIR (Alt)	AIDI (Alt)
0.00%	0.99	NN	NaN	NaN	1.23	NN	NaN
20.00%	2.19	NN	NaN	NaN	2.42	NN	NaN
40.00%	3.39	NN	NaN	NaN	3.5	NN	NaN
60.00%	4.64	NN	1.86	NaN	4.6	NN	2.28
80.00%	5.75	NN	2.7	2.17	5.84	NN	3.93
100.00%	6.97	NN	3.04	3.35	7.13	1.66	5.68

NN = Necessity Not reached.

Tab. 8 reports detailed statistics on the bottlenecks of Economic Performance and REI by percentiles of AIR and AIDI. At the 0.00% percentile The Benchmark Economic Performance is 1 at Base and it depicts that the REI is in early stage at 1.22. By the 20. *y* 245 percentiles, Economic Performance raises to 2.2, showing that it is gradually growing thus changing the REI to 2.38. At the 40. cents percentile, Economic Performance attains the level of 3.4, with increases in REI to 3 but the option the condition remains constant indicates stability in this area. 53. By the 60. Again, in essence, the Economic Performance jumps to the 4th percentile from 00% percentile. 5, and for $x = 6$, AIR begins to rise and has a value of 1.88, This indicates that the objective of the study becomes crucial at this stage. Also, AIDI comes out to be equal to 2 as the false positive rate is reduced. 28, points to the increased impact of the recommendation on REI, with which it already reached number 4.68. At the 80.00% percentile, Economic Performance increases to 5. The Economic Performance mean statement can therefore be concluded as follows: 8, with significant improvements in all indexes inclusive of REI; the AIDI value rose to 2.19 and 3.96 respectively. Finally, at the 100.00% percentile, the economic performance attains its maximum score of 7 on the REI scale too, AIR is 1.66, while AIDI is 5.64. These patterns indicate that Economic Performance and REI can be initially improved without high levels of AIR and AIDI while the higher stages of economic and innovation performance have a reliant connection with AII and IR. This highlights the need to nurture AI to minimize the bottlenecks to get the best results concerning the economy and innovations.

Table 9 Mediation analysis results

Pathway	Coefficient	Standard Error	t-value	p-value
AIDI → REI	0.48	0.085	5.5	0.00
REI → Economic Performance	0.35	0.09	3.9	0.00
AIDI → REI → Economic Performance (Indirect)	0.168	0.04	4.2	0.00
Total Effect (AIDI → Economic Performance)	0.518	0.07	7.4	0.00

Tab. 9 displays the mediation results concerning the AIDI, REI, and Economic Performance variables. Analyzing the coefficients of the direct effects originating from AIDI to REI, there is a positive coefficient amounting to 0. This indicates that AI-driven innovation significantly supports real economy innovation which has been confirmed from the knock off value of 48 with $t = 5.5$, $p < 0.001$. Then, Economic Performance is significantly positively affected by REI, an aspect that stands at a coefficient of 0.35 ($t = 3.9$, $p < 0.001$) which implies that the degree of economic innovation has an indirect positive correlation on the economic performance. Self-generated: The coefficient of AIDI is also significant to Economic Performance through REI indirectly while having a coefficient of 0., thus supporting the hypothesis that the AIDI has a significant relationship with Economic Performance partially through REI [$t = 4.2$, $p < 0.001$; $\beta = 0.168$]. This mediation effect draws attention to the social role of economic innovation as the link through which the application of AI advances economic performance. The direct and indirect impact of AIDI on Economic Performance together is also very large and significant with a coefficient of 0.518 ($t = 7.4$, $p < 0.001$). These findings would further cement the role of AI innovation in the economic performance and in its contribution to economic innovation. Thus, Fig. 3 shows that Real Economy Innovation (REI) partially mediates the positive impact of the dependent variable, AI-Driven Innovation (AIDI) on the independent variable, Economic Performance. In this model, AIDI is the independent variable while Economic Performance is the dependent variable with REI mediating the relationship, the path coefficients reveal the nature and degree of the impact.

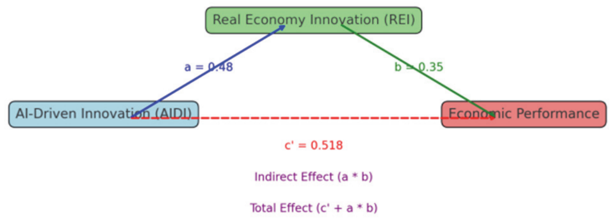

Figure 3 Mediation effect of real economy innovation

Table 10 Moderator analysis results

Pathway	Coefficient	Standard Error	*t*-value	*p*-value
AIDI → Economic Performance	0.17	0.09	1.89	0.03
AIR x AIDI → Economic Performance	0.063	0.028	1.2	0.15
Total Effect	0.233	0.08	2.913	0.004

The below table is Tab. 10 which shows the test for the moderator analysis that measures the moderation role of AII Readiness (AIR) on the antecedent of the research variable, AI-Driven Innovation (AIDI) and economic performance. The direct arrows from AIDI to Economic Performance display a positive coefficient of 0.17 ($t = 1.89$, $p = 0.03$) which shows that AI youths were right in advancing the perception that AI driven innovation is positive to economic performance. Self-generated Economic Performance as a function of AIR and AIDI, thus, is insignificant with a value of 0. Mean = 0.063 ($t = 1.2$, $p = 0.15$), hence implying that our construct, AI readiness does not contend this relationship. The grossed-up impact of AIDI and the interaction with AIR on Economic Performance is "sizeable" and "statistically significant" with a coefficient score of 0.233, $t = 2.913$, $p = 0.004$. AI innovations' moderation by AI readiness reveals that while AI innovations essentiated alone have a significant impact on the supply side economic performance, AI readiness, albeit as a moderate variable, has a positive impact on the degree of improvement of the economic outcomes stimulated by AI innovations.

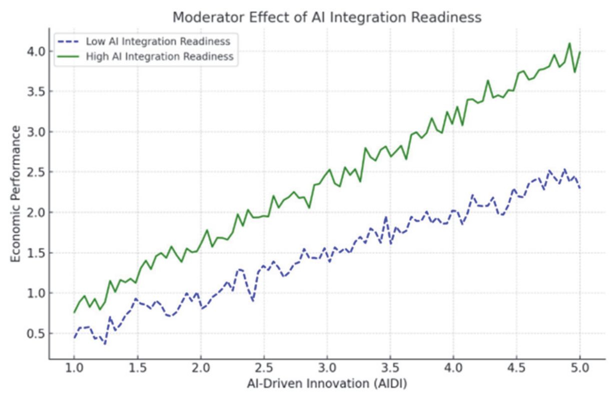

Figure 4 Moderator effect of AII readiness

Therefore, Fig. 4 represent the relationship between AIDI and economic performance moderated by AII Readiness (AIR). This figure presents the low level of AIR on one line and the high level of AIR on the second one. From the analysis, it can be deduced that the coefficients between AIDI and Economic Performance are higher when AIR is high; hence, the firms with higher readiness scores for the integration of AI have better economic performances when it comes to innovations prompted by the application of the technology.

5 DISCUSSION

5.1 Practical Implications

The incorporation of artificial intelligence or AI into the real economy and how it affects productivity, innovation, and economic performance: The results of this study therefore stress that AI is not a simple case of overproduction and consumptive deficit but a complex entity with the power to boost the economy in direct and indirect ways. Therefore, the findings of the hypothesis testing, mediation, and moderator analyses give a more detailed picture of the effect of AI-driven innovation, economic innovation, and AI readiness on economic performance. Among various empirical patterns identified, the evidence of a very high and positive linear correlation between AIDI and Economic Performance may be mentioned. In line with Brynjolfsson et al. (2018) study, they highlighted that productivity gains are significant in the companies that adopt AI technologies. The first model that explains how AIDI influences Economic Performance has the largest coefficient of 0.17, showing the worth and relevance of AI in making improvements to operations that the competitive edge, however, required. All these areas in which AI can perform various tasks meant for resource optimization and decision-making have a direct impact on the economics of firms. The mediation analysis also provides a breakdown of results that shows that the Real Economy Innovation (REI) acts as a mediator that helps explain how the AI innovation impacts the economy. Thus, it is evident that AIDI has a reasonably significant indirect effect on Economic Performance, mediated through the REI construct with a coefficient of 0.168, providing the understanding that economic innovation can be viewed as an important transmission or delivery mechanism. This discovery also echoes the views of Chesbrough and Rosenbloom (2002) that hold that for maximum value to be realized from a technological advancement, localized business model innovations must arise. The adoption of Artificial Intelligence within the technologies available for economic improvement is a major area of advancement in boosting economic returns, thus showing the need to develop an innovative environment within firms.

This paper also focuses on AII Readiness (AIR) as a mediator between the role of AI driven innovation and economic development. Thus, while the interaction of AIR by AIDI had no take on the Economic Performance, the total impact of AIDI, when compounded by AIR was fairly impressive. This implies that although AI readiness by itself is unlikely to significantly change the effect of concluded AI innovation on the magnitude of savings, it increases the combined effect of AI on the performance of the economy. This has been supported by Teece et al.

(1997) where they defined the concept of dynamic capabilities indicating that the ability to integrate, create and reconfigure internal and external competencies was critical to firms' ability to obtain competitive advantage in dynamic environment. Nevertheless, the paper also reveals some drawbacks that come together with the AI implementation. As it is shown from the above results, the effects of AIR are negative on both Economic Performance and REI with the coefficients being −0.15 and −0.19 respectively, suggesting certain problems that firms can experience on their way towards AI-based organization. These results align with the issues discussed by Bessen (2019) that identified that the positive effect of AI is unequally distributed and firms with small capital and mild capabilities can find it more difficult to adopt AI. This goes to show that appropriate interventions are required to overcome those challenges that firms, especially SMEs, face to harness AI technologies to the optimum.

Also, the correlation matrix and discriminant validity show that AI readiness, related innovation, and a country's economic performance are closely linked. The substantial significant coefficients of the variables AII Readiness, AI-Driven Innovation and Economic Performance have highlighted the presence of interactive effects. Companies that are in a better position to adopt and integrate with the help of AI, are those that offer more innovative products, and therefore, achieve more favorable economic performance. This is in consonance with Parker et al. (2016) [48] on the need to be platform ready in any technological advancement. The MNCA and bottleneck analysis give further information on the necessary conditions for achieving the highest level of economic output. As evidenced from the results of regressing AIDI and REI to Economic Performance, innovation is a crucial factor in the process of economic development. The bottleneck analysis also demonstrates that even if economic performance and innovation's initial development do not require high AIR and AIDI indicators, further performance stages are critically dependent on additional AI development and Innovation preparedness. This underlines the need to develop AI capacity and preparedness to surmount challenges and obtain best value for economic activities.

The implications of this study are as follows offering practical insights for policies, business people, and other parties interested in economic benefits of AI. Concisely, the implication of this study is that the integration of AI has diverse consequences on economic performance hence a guide to implementing AI technologies across industries but more especially for SMEs. Secondly, overall, the statistical results found that the variables of AI-driven innovation have a highly positive correlation with the economic performance, which means that the business community must embrace AI technologies. The application of AI in the company's processes can lead to better performance, efficient usage of resources, and improved decision-making. Hence, it is heralded that business managers should embrace AI-led solutions to be relevant and improve on their economic performances. This means incorporating AI into business and development strategies but also cultivating openness to learning and refining new methods.

5.2 Policy Recommendation

That is why Real Economy Innovation (REI) is meditating the correlation between AI-driven innovation and an economic performance expressing the need to develop innovative business models. The attention should be paid to the change in value creation and delivery archetypes to optimize the potential of AI. This is in concordance to the dynamic capabilities perspective which presents business firms as needing to adapt the methods of value creation to maintain competitive benefit over time in a volatile environment. Thus, businesses can secure the benefits of innovations with the help of Artificial Intelligence in terms of increasing their economic outcomes. This study identified another culture level dimension named the AII Readiness (AIR), which improves the effect of AI-based innovation on economic performance. Nevertheless, the problems related to AI readiness and their distribution reveal the necessity of focused assistance, especially with regards to SMEs. Following China's 2022 MIIT "AI + SMEs" Action Plan, we recommend matching subsidies of up to RMB 1 million per pilot project for cloud-based AI, combined with 50% tax credit on AI software leasing and loan guarantees covering 70% of the principal for AI-related working capital. This cohesiveness indicates that the role of public private partnerships can go a long way in helping in knowledge transfer and diffusion of innovation with regards to the benefits of Artificial Intelligence. In this way, with the help of the outlined list of activities for supporting SMEs in AI implementation, policymakers can address the issue of the widening existing gap in the economy. It is suggested that the green AI indicator (kWh saved / 10,000 yuan revenue) be included in the MIIT subsidy assessment to promote the simultaneous improvement of economic performance and carbon performance.

Thus, negative influence of readiness for AI on economic performance and REI indicates lessons during transition to AI operations. However, this implies that firms may encounter efficient implementation difficulties or inherently bad transitional implementations that can generate poor company performance. To reduce these risks business ought to implement a prototyping approach to the adoption of AI where the adoption starts from a pilot basis. To consider the AI-related issues at their initial stages, it is crucial to perform the subsequent steps: Also, creating a culture of firms and their affiliates working together and one being able to see and learn from the other's experiences can go a long way in easing the process. The presence of reportedly high levels of AI readiness, innovation, and economic performance is tightly linked with each other. In other words, more technologically ready firms are more innovative and, therefore, have superior economic performance. This indicates that while businesses need to obtain AI technologies, they should also develop their preparedness for the integration of AI. This entails creating the appropriate talent, environment, and firm structures that are conducive for implementing and exploiting AI solutions. Thus, increasing their AI readiness, the firms can achieve the greatest outcomes of the AI-driven innovation as well as contribute to the long-term development of the economy.

6 CONCLUSION

6.1 Limitations

Using frugal innovation, Business Model Innovation and AII Readiness as the moderators, this research has endeavored to examine the effects of Integrated AI on economic performance. Applying a sound quantitative research methodology, the investigation extended to 177 firms of different types, paying much attention to SMEs. The research emphasizes the positivist correlation between automation processes brought by AI and economic results on a large scale. These technologies affect efficiency whereby existing resources are utilized optimally; decision making is also affected through improving the economic performance of the firms. This speaks volumes of the need for business to embrace AI solutions and integrate innovation as a constant process.

Thus, Real Economy Innovation (REI) appeared to play a significant role as a mediator in this regard and emphasized the need for firms to adapt novel business models to capitalize on AI. This involves the constant fluidity between artificial intelligence innovation on the one hand, and economic performance indicators on the other, which are enabled by REI; suggesting that the integration of technology and business model innovations into a society's post-industrial economy should be carefully planned for. This research designated the dependency as the AII Readiness (AIR) since it is central to improving the outcomes of AI on economic performance. Thus, the difficulties observed concerning AI readiness, especially regarding SMEs, suggest that policymakers need to assist and promote AI more effectively. Ministers of the SMILE Declaration agreed that funding, education, and supporting infrastructures improvements are the main needs for SMEs to remove the barriers of the AI and enable inclusive progress. The study also shows that there is likelihood of encountering challenges during transformation to the use of artificial intelligence, which is elaborated by the lack of strong relationship between AI readiness and performance. This seems to indicate that AI implementation may pose various implementation issues that require the resolution through employing a progressive strategy in implementing AI and conducting regular assessments and reviews of the AI undertaking by firms.

However, it is also pertinent here to note some of the main limitations which have been observed in this study, although they are not very serious in nature. Firstly, it uses only secondary sources, which decreases its reliability because these sources can contain bias or mistakes inherited from the primary data collection stage. Despite attempts to control the amount of variability from popular and well-respected sources such as industry reports and the World Bank, and Organization for Economic Cooperation and Development (OECD) databases to obtain the data, there might be inconsistency in the quality of data obtained from these sources. Future work can also use more positive methods of data collection such as interviews to increase the validity of the conclusions. One thing to be aware of is that the data is cross-sectional, which means that growth points are monitored at a single point in time and not over time. This decision hampers cause-and-effect relationships when determining impact of the integration of AI on economic performance. Cross-sectional investigations give the investigate results of the firms at a certain time, more comprehensive and convincing evidences of the casual relationships and chronic effects brought by the AI adopting. Such studies could also capture the dynamic nature of AII and its effects as the various factors influencing its performance change over time.

6.2 Future Research

This research mainly targets small and medium-sized enterprises (SMEs), though they play an essential role in the economy, their results are not necessarily generalizable to large organizations endowed with additional capacities for AI implementation. The study should again use a sample of firms of different sizes so that there can be comparative reviews of the different firms regarding their integration of AI. Further, industry-level research might help to focus more on the specifics related to the applications of AI technologies in various sectors. The result presented in this study does signal some possible transitional challenges that firms may encounter regarding the negative effect of readiness on performance and innovation. However, the causes for these negative impacts were not fully elaborated on, implying that there are even more. Future research should explore more details about those challenges' causes, including the barriers to implementing EBP and the EBP implementation problems. It might be beneficial to identify these factors for the creation of approaches to prevent common transitional obstacles as well as to improve the general preparedness for using AI.

In addition, despite being found to moderate the relationship of AI driven Innovation on economic performance, the level of moderating influence of AII Readiness (AIR) was not as powerful as expected. This implies that there is a need to establish other moderating factors that may affect this relationship. The practice enablers and inhibitors could have explored the other features like culture, leadership support, workers' skills and training that can broaden the understanding of the research. Geographical diversification was not very broad, and in some parts of the study, it may be assigned that this reduces the scope of the study by limiting research results to regions with dissimilar technologies and levels of economic development. Further studies should therefore focus on conducting surveys with a more diverse geographical population to see the effect of region on the use of AI and its economic effects. Comparative analysis of countries and regions could be useful in identifying which conditions enable or prevent organizations from adopting AI solutions.

7 REFERENCES

[1] Brynjolfsson, E. & McAfee, A. (2017). Machine, platform, crowd: Harnessing our digital future. *WW New York: Norton & Company*, *564*, 45-49.

[2] Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., & Malhotra, S. (2018). Notes from the AI frontier: Insights from hundreds of use cases. *McKinsey Global Institute*, *2*, 267.

[3] Lee, J., X. Grey, M., Ha, S., Kunz, T., Jain, S., Ye, Y., Karen Liu, C. et al. (2018). Dart: Dynamic animation and robotics

toolkit. *The Journal of Open Source Software*, *3*(22), 500. https://doi.org/10.21105/joss.00500

[4] Acemoglu, D. & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of economic perspectives*, *33*(2), 3-30. https://doi.org/10.1257/jep.33.2.3

[5] Radjou, N. & Prabhu, J. (2015). *Frugal Innovation: How to do more with less*. The Economist.

[6] Moorhouse, T. P., Balaskas, M., D'Cruze, N. C., & Macdonald, D. W. (2017). Information could reduce consumer demand for exotic pets. *Conservation Letters*, *10*(3), 337-345. https://doi.org/10.1111/conl.12326

[7] Govindan, K. (2022). How artificial intelligence drives sustainable frugal innovation: A multitheoretical perspective. *IEEE Transactions on Engineering Management*, *71*, 638-655. https://doi.org/10.1109/TEM.2021.3116187

[8] Teece, D. J. (2018). Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Research policy*, *47*(8), 1367-1387. https://doi.org/10.1016/j.respol.2018.05.003

[9] Rust, R. T. & Huang, M. H. (2014). The service revolution and the transformation of marketing science. *Marketing Science*, *33*(2), 206-221. https://doi.org/10.1287/mksc.2014.0863

[10] Dima, A., Bugheanu, A. M., Dinulescu, R., Potcovaru, A. M., Stefanescu, C. A., & Marin, I. (2022). Exploring the research regarding frugal innovation and business sustainability through bibliometric analysis. *Sustainability*, *14*(3), 1326. https://doi.org/10.3390/su14031326

[11] Qin, W. (2024). How to unleash frugal innovation through internet of things and artificial intelligence: Moderating role of entrepreneurial knowledge and future challenges. *Technological Forecasting and Social Change*, *202*, 123286. https://doi.org/10.1016/j.techfore.2023.123286

[12] Bessen, J. (2019). Automation and jobs: When technology boosts employment. *Economic Policy*, *34*(100), 589-626. https://doi.org/10.1093/epolic/eiaa001

[13] Aghion, P., Akcigit, U., Bergeaud, A., Blundell, R., & Hémous, D. (2019). Innovation and top income inequality. *The Review of Economic Studies*, *86*(1), 1-45. https://doi.org/10.1093/restud/rdy027

[14] Floridi, L. & Cowls, J. (2022). A unified framework of five principles for AI in society. *Machine learning and the city: Applications in architecture and urban design*, 535-545. https://doi.org/10.1002/9781119815075.ch45

[15] Taddeo, M. & Floridi, L. (2018). How AI can be a force for good. *Science*, *361*(6404), 751-752. https://doi.org/10.1126/science.aat5991

[16] Rogers, E. M. & Singhal, A. (2003). Empowerment and communication: Lessons learned from organizing for social change. *Annals of the International Communication Association*, *27*(1), 67-85. https://doi.org/10.1080/23808985.2003.11679022

[17] Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of management*, *17*(1), 99-120. https://doi.org/10.1177/014920639101700108

[18] Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, *18*(7), 509-533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

[19] Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox. *The economics of artificial intelligence: An agenda*, *23*, 23-57. https://doi.org/10.7208/chicago/9780226613475.003.0001

[20] Masanja, N. & Mkumbo, H. (2020). The application of open source artificial intelligence as an approach to frugal innovation in Tanzania. *Journal: International Journal of Research and Innovation in Applied Science*, 5(3), 2454-6194.

[21] Saleem, I., Al-Breiki, N. S. S., & Asad, M. (2024). The nexus of artificial intelligence, frugal innovation and business model innovation to nurture internationalization: A survey of SME's readiness. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(3), 100326. https://doi.org/10.1016/j.joitmc.2024.100326

[22] De Waal, G. A., Thangarajah, J., & McMurray, A. J. (2020). Artificial intelligence and frugal innovation: A formidable alliance in future education. *Management and business education in the time of artificial intelligence*, 55-76.

[23] Leliveld, A. & Knorringa, P. (2018). Frugal innovation and development research. *The European Journal of Development Research*, *30*, 1-16. https://doi.org/10.1057/s41287-017-0121-4

[24] Tesic, S., Bajic, B., Cosic, I., & Rikalovic, A. (2021). Frugal Innovations in Industry 4.0: The Identification of Key Indicators. *Annals of DAAAM & Proceedings*. https://doi.org/10.2507/32nd.daaam.proceedings.037

[25] Ebolor, A., Agarwal, N., & Brem, A. (2022). Fostering the Sustainable Development Goals with technologies underpinned by frugal innovation. *International Journal of Technology Management*, *88*(2-4), 155-174. https://doi.org/10.1504/IJTM.2022.121503

[26] Alliance, A. (2020). Artificial intelligence and frugal innovation. *Management and Business Education in the Time of Artificial Intelligence*, 55-76.

[27] Barton, D. (2018). McKinsey Quarterly 2018 Number 2: Overview and full issue. *The McKinsey Quarterly*.

[28] Wang, J., Lu, Y., Fan, S., Hu, P., & Wang, B. (2022). How to survive in the age of artificial intelligence? Exploring the intelligent transformations of SMEs in central China. *International Journal of Emerging Markets*, *17*(4), 1143-1162. https://doi.org/10.1108/IJOEM-06-2021-0985

[29] Borah, S., Kama, C., Rakshit, S., & Vajjhala, N. R. (2022). Applications of artificial intelligence in small-and medium-sized enterprises (SMEs). *Cognitive Informatics and Soft Computing: Proceeding of CISC 2021*, 717-726. https://doi.org/10.1007/978-981-16-8763-1_59

[30] Abrokwah-Larbi, K. & Awuku-Larbi, Y. (2024). The impact of artificial intelligence in marketing on the performance of business organizations: evidence from SMEs in an emerging economy. *Journal of Entrepreneurship in Emerging Economies*, *16*(4), 1090-1117. https://doi.org/10.1108/JEEE-07-2022-0207

[31] Arranz, C. F., Arroyabe, M. F., Arranz, N., & de Arroyabe, J. C. F. (2023). Digitalisation dynamics in SMEs: An approach from systems dynamics and artificial intelligence. *Technological Forecasting and Social Change*, *196*, 122880. https://doi.org/10.1016/j.techfore.2023.122880

[32] Žigienė, G., Rybakovas, E., & Alzbutas, R. (2019). Artificial intelligence based commercial risk management framework for SMEs. *Sustainability*, *11*(16), 4501. https://doi.org/10.3390/su11164501

[33] Baabdullah, A. M., Alalwan, A. A., Slade, E. L., Raman, R., & Khatatneh, K. F. (2021). SMEs and artificial intelligence (AI): Antecedents and consequences of AI-based B2B practices. *Industrial Marketing Management*, *98*, 255-270. https://doi.org/10.1016/j.indmarman.2021.09.003

[34] Wei, R. & Pardo, C. (2022). Artificial intelligence and SMEs: How can B2B SMEs leverage AI platforms to integrate AI technologies? *Industrial Marketing Management*, *107*, 466-483. https://doi.org/10.1016/j.indmarman.2022.10.008

[35] Rawashdeh, A., Bakhit, M., & Abaalkhail, L. (2023). Determinants of artificial intelligence adoption in SMEs: The mediating role of accounting automation. *International Journal of Data and Network Science*, *7*(1), 25-34. https://doi.org/10.5267/j.ijdns.2022.12.010

[36] Sharma, S., Singh, G., Islam, N., & Dhir, A. (2022). Why do SMEs adopt artificial intelligence-based chatbots? *IEEE Transactions on Engineering Management*, *71*, 1773-1786. https://doi.org/10.1109/TEM.2022.3203469

[37] Drydakis, N. (2022). Artificial Intelligence and reduced SMEs' business risks. A dynamic capabilities analysis during the COVID-19 pandemic. *Information Systems Frontiers*, *24*(4), 1223-1247. https://doi.org/10.1007/s10796-022-10249-6

[38] Akbar, A., Mustafa, M., Haeruddin, M., Mariñas-Acosta, C., Hasbiyadi, H., Alam, S., & Darmawinata, W. N. S. (2024). Days of future past: Scrutinising the artificial intelligence impact on the leadership of internationalising SMEs. *Asian Journal of Economics, Business and Accounting*, *24*(5), 53-59. https://doi.org/10.9734/ajeba/2024/v24i51292

[39] OECD. (2019). An OECD Learning Framework 2030. *The Future of Education and Labor*, 23-35. https://doi.org/10.1007/978-3-030-26068-2_3

[40] Peretz-Andersson, E., Tabares, S., Mikalef, P., & Parida, V. (2024). Artificial intelligence implementation in manufacturing SMEs: A resource orchestration approach. *International Journal of Information Management*, *77*, 102781. https://doi.org/10.1016/j.ijinfomgt.2024.102781

[41] Khan, A. A., Laghari, A. A., Li, P., Dootio, M. A., & Karim, S. (2023). The collaborative role of blockchain, artificial intelligence, and industrial internet of things in digitalization of small and medium-size enterprises. *Scientific Reports*, *13*(1), 1656. https://doi.org/10.1038/s41598-023-28707-9

[42] Kaplan, R. S. & Norton, D. P. (1992). *The balanced scorecard: measures that drive performance*.

[43] Brynjolfsson, E. & McAfee, A. (2017). Machine, platform, crowd: Harnessing our digital future. *WW New York: Norton & Company*, *564*.

[44] Radjou, N. & Prabhu, J. (2015). *Frugal Innovation: How to do more with less*. The Economist.

[45] Chesbrough, H. & Rosenbloom, R. S. (2002). The role of the business model in capturing value from innovation: evidence from Xerox Corporation's technology spin-off companies. *Industrial and corporate change*, *11*(3), 529-555. https://doi.org/10.1093/icc/11.3.529

[46] Pavitt, K. (1984). Sectoral patterns of technical change: towards a taxonomy and a theory. *Research policy*, *13*(6), 343-373. https://doi.org/10.1016/0048-7333(84)90018-0

[47] Porter, M. E. (1991). Towards a dynamic theory of strategy. *Strategic management journal*, *12*(S2), 95-117. https://doi.org/10.1002/smj.4250121008

[48] Parker, G. G., Van Alstyne, M. W., & Choudary, S. P. (2016). *Platform revolution: How networked markets are transforming the economy and how to make them work for you*. WW Norton & Company.

[49] OECD/Eurostat (2018). *Oslo Manual 2018: Guidelines for Collecting, Reporting and Using Data on Innovation, 4th Edition, the Measurement of Scientific, Technological and Innovation Activities*. OECD Publishing, Paris. https://doi.org/10.1787/9789264304604-en

Contact information:

Qinghua LI
(Corresponding author)
College of Digital Economy,
Yantai Nanshan University,
Yantai Shandong, 265713, China
E-mail: lnsylqh@163.com

Meiyan SUI
College of Digital Economy,
Yantai Nanshan University,
Yantai Shandong, 265713, China

Aining LI
College of Management Engineering,
Yantai Nanshan University,
Yantai Shandong, 265713, China

Yanzhi ZHANG
College of Technology and Data,
Yantai Nanshan University,
Yantai Shandong, 265713, China

Hongmei XU
College of Digital Economy,
Yantai Nanshan University,
Yantai Shandong, 265713, China