sustainability

MDPI

Article

Population Aging, Industrial Intelligence and Export Technology Complexity

Kexu Wu [1], Zhiwei Tang [2] and Longpeng Zhang [2,*]

[1] School of Management and Economics, University of Electronic Science and Technology of China, Chengdu 611731, China
[2] School of Public Affairs and Administration, University of Electronic Science and Technology of China, Chengdu 611731, China
* Correspondence: zlp1988@uestc.edu.cn

Abstract: The ageing of the population has become a serious test for all countries and regions, and industrial intelligence, as a new development model that integrates traditional industries with modern technology, will contribute to the deep integration of the industrial and innovation chains and thus to the enhancement of national core competitiveness. Based on the dual influence of population ageing and industrial intelligence, this paper uses the 2016 version of the World Input-Output Database (WIOD) data for 16 manufacturing industries in 43 countries from 2000 to 2014 to construct an econometric regression model to empirically test the relationship between population ageing, industrial intelligence and technological complexity of exports. The results of the study show, firstly, that population ageing plays a positive role in the technical complexity of exports. Secondly, the introduction of industrial intelligence mitigates the adverse effects of an ageing population through a complementary substitution mechanism on the one hand, and promotes industrial upgrading and transformation through the infiltration and expansion effects of industrial intelligence on the other, which in turn has a positive impact on the increase in technological sophistication of exports. In addition, the paper further divides the level of industry technology, the level of national development and the age structure of the ageing population, and explores the impact of industry intelligence in different dimensions. The results show that industrial intelligence can have a positive impact on export technological sophistication at the industry level, at the national level and in terms of ageing demographics. The research results provide a new way of thinking, through which countries around the world can formulate population policies and industrial policies and improve the complexity of export technology under the background of aging.

Keywords: population aging; artificial intelligence; industrial intelligence; export technology complexity

check for updates

Citation: Wu, K.; Tang, Z.; Zhang, L. Population Aging, Industrial Intelligence and Export Technology Complexity. *Sustainability* **2022**, *14*, 13600. https://doi.org/10.3390/su142013600

Academic Editors: Babek Erdebilli (B.D Rouyendegh) and Erfan Babaee Tirkolaee

Received: 2 September 2022
Accepted: 17 October 2022
Published: 20 October 2022

1. Introduction

The current issue of population aging is a severe test being faced by countries around the world [1]. According to the 2019 edition of the United Nations' World Population Prospects, the world's rate of population growth rate gradually slowed down after reaching its peak in 1965–1970 [2]. Between 2010 and 2020, the population growth rate dropped below 1.1% for the first time. The United Nations predicts that the slowdown will continue until the end of this century [2]. At the same time, in 2018, due to the slowdown in the birth rate, for the first time in human history the number of people over the age of 65 exceeded the number of children; the age structure of the population has undergone dramatic changes. In 2019, the proportion of the elderly population to the total population in most countries in the world had more than tripled (compared with 1990); the global population structure has gradually changed from a young society to an aging society [3]. This aging population brings both challenges and new opportunities [4]. In terms of challenges, some studies have pointed out that the intensification of population aging has led to a shortage of labor market supply [5]. Simultaneously, the aging population has greatly increased the pension burden on families and society [6], and has also put forward higher requirements for the supply, efficiency and quality of public services [7]. From another perspective, some researchers believe that the aging population has put forward higher requirements for the supply of products in the consumer goods market, thereby promoting the progress of technology, almost in disguise [8]. Through the adjustment of the current retirement policy, this segment of high-quality labor resources can be fully utilized, and the national export technology level can be improved [9].

As the global demographic structure changes, the past economic development model, which focused on labour-intensive industries, is no longer applicable to the current technology-led green development model [10]. By adjusting the industrial development model, reducing the dependence of industry on the population has become the main strategy employed by current governments to promote their own economic development [11]. For this reason, the intelligent transformation of industry based on the application of smart technology is gradually receiving a great deal of attention from various countries around the world [12]. Nguyen points out that the development mode of integrating the Internet, big data, artificial intelligence and real industries has become the mainstream of industrial intelligence development [13]. This model will have broader and far-reaching impacts on the world economy [13]. According to statistics from the International Federation of Robotics, the number of newly-installed industrial robots worldwide increased from 111,000 units in 2006, to 373,000 units in 2019, an annual growth rate of 10.56% [14]. Meanwhile, from 2006 to 2019, the population growth rate dropped from 1.24% to 1.07%. At the same time, McKinsey & Company have predicted that the application of industrial intelligent technology between 2020 and 2030 will contribute 1.2% to the improvement of industrial efficiency [15]. By 2030, intelligent technology is expected to make a huge contribution to global economic output [15].

Hajkowicz, after conducting a study on the development and application of artificial intelligence technologies in Australia, points out that the increase in the level of industrial intelligence can help to solve some of the economic development problems that currently exist [16]. For example, through the support of massive data flow and algorithms, the problem of information asymmetry can be effectively reduced, and the accuracy of decision-making can be improved [17]. Using the characteristics of the Internet can help to promote: intra-industry and inter-industry connections, inter-industry coordination and cooperation, and the development of the industrial structure to a high level [18]. At the same time, through industrial intelligence, the fairness and efficiency of social behaviors from production to distribution to exchange and consumption will be promoted, all of which will have a positive impact on social development [19]. In addition, the development of industrial intelligence has also already played an important role in increasing the technical complexity of exports [20]. Factors such as production equipment and product quality are essentially realized through the channel of industrial intelligence in the process of affecting the technical complexity of exports [20]. Also, with the continuous improvement in the level of information technology, the positive role of industrial intelligence in R&D innovation has become increasingly obvious [21]. Industrial intelligence has also become an increasingly important means to promote the construction of an innovative country and promote economic development [22].

In the context of an increasing ageing population and the transformation of national industries into intelligent ones, this paper examines whether industrial intelligence can contribute to an increase in the technological complexity of exports in the context of an ageing population. Hausmann first proposed the concept of "export technology complexity" [23], which reflects the important economic characteristics of a country's export technology content, production efficiency, and export structure. The improvement of export technology complexity will help industrial upgrading and enhance national comprehensive competitiveness. To date, most of the research in this field has focused on the factors that influence export technology complexity. Far less research has been carried out on the combination of population aging, industrial intelligence and export technology complexity. Therefore, this paper will thus objectively evaluate the impact of population ageing on the technological complexity of exports and, on this basis, discuss the mediating effect of industrial intelligence in the impact of population ageing and the technological complexity of exports. In the context of the increasingly serious problem of ageing, the findings of this study help to improve the academic research on ageing and provide some ideas for countries to deal with the problem of ageing, adjust the structure of export trade and the direction of development of the manufacturing industry, so this study has certain theoretical and practical significance. In addition, this paper uses cross-country data on manufacturing industry segments to conduct an empirical study, and further classifies the technological content of the industry and the level of development of the country, allowing the paper to explore the relationship between population ageing, industrial intelligence and export technological complexity in more detail, and to draw more relevant and revealing conclusions that will help to further expand the marginal contribution of this paper.

2. Literature Review and Critique

2.1. Literature Review

Current academic research on population aging, industrial intelligence and export technology complexity can be summarized into three aspects. First of all, in terms of changes in population structure and related research on export trade, early literature content mainly focused on the research between the age structure of the population and the transaction items that often occur in the balance of payments [24]. The current body of research mainly focuses on the aging of the population, the impact of the population's transformation on export comparative advantage, export quality upgrade, and trade structure [25].

In terms of the impact of aging on the current account, Coale & Hoover believed that an increase in the social dependency ratio would lead to an excessively low savings rate and an excessively high consumption rate [26]. In terms of export trade, the study maintained that a current account deficit would appear, and based on this, the researchers put forward the "support burden hypothesis" [26]. However, the findings of Fougère and Mérette are diametrically opposed to this, with their findings suggesting that ageing has a positive effect on improving the current account balance [27]. The conflict between the above two viewpoints has led to further research on this issue in academic circles. Using the population dependency ratio as a measure of population ageing, Chinn & Prasad find that the ageing of a country's population has a negative impact on the current account [28]. Kim & Lee studied the changes in the demographic structure of Southeast Asian countries and found that, when the population structure is aging, goods, services, income and current transfers show negative growth [29]. However, Gruber & Kamin studied the changes of the current account-to-GDP ratio in 61 countries, from 1982 to 2003 [30]. The study found that the age structure of the population cannot explain the huge surpluses of Asian countries [30].

In terms of research on the impact of aging on the structure of export trade, Sayan was the first to study the relationship between population aging and national trade patterns [31]. The study used an OLG model to analyze the aging degree of the population represented by the decrease in the birth rate of the population. The authors concluded that population aging increases capital in a country or region, but labor becomes a scarce commodity [31]. As a result, the relative price of capital-intensive commodities in the country is reduced, and the export comparative advantage of capital-intensive commodities is increased. On the basis of Sayan's research, Naito & Zhao concluded that, once free trade reaches a stable level, countries with a high degree of aging will use capital-intensive commodities as their main export products [32]. Meanwhile, non-aging countries will make themselves endogenous and become an economic power that can dominate international prices [32]. Yakita based his study on the "H-O" model and introduced per capita life expectancy extension and human capital investment [33]. The study's results show that there is not necessarily a relationship between the degree of countries' population aging and the export of capital-intensive products from those countries [33]. Zuo & Yang believed that the number of China's labor force will decrease sharply in line with the aging of the population [34]. In addition, the current "demographic dividend" will disappear, which will change the comparative advantage of exports. Tian et al. demonstrate that the population dependency ratio has a significant effect on bilateral trade using data from 176 countries for the period 1970–2006 [35]. Graetz & Michel conclude from an assessment of population mobility and population size projections that inconsistencies in the degree of population ageing across countries will lead to mutually beneficial trade effects in the context of international capital flows [36]. By comparing the export trade structure of two large population countries, China and India, Wang et al. find that a country with a higher degree of population ageing tends to favour export trade in goods with higher technology content in its export trade structure, while a large population country with a lower degree of ageing focuses more on exports of labour-intensive goods [37]. Brockova et al. study export trade in China in the era of the 'new normal' [38]. Their findings suggest that, as China's population ages, the country's export trade has shifted from the traditional primary sector to the secondary and tertiary sectors, and the structure of export trade has gradually changed from 'processing' to 'innovation' [38]. A study by Wu et al. found that increasing levels of population ageing have a more severe impact on developing countries compared to developed countries [39]. The impact of population ageing on the decline in autonomous innovation capacity and the rise in human capital leads to a shift in the structure of export trade towards lower technology levels in developing countries with higher levels of population ageing [39].

The second aspect pertains to the research on the economic effects of industrial intelligence, which mainly focuses on the impact of industrial intelligence on total factor productivity.

As the early definition of industrial intelligence in academia mainly focuses on traditional communication technologies such as industrial information processing, industrial information services and industrial information equipment, it does not involve modern intelligent technologies such as big data, the Internet of Things and Artificial Intelligence [40]. Therefore, the early research on industrial intelligence focused on the relationship between traditional information technology and total factor productivity. For example, Lichtenberg conducted an empirical study using the data of American enterprises in the three years from 1988 to 1991 as a research sample [41]. Shao & Lin also took American companies as the research object [42]. That study analyzed the relationship between the level of information technology investment and total factor productivity and found that a positive correlation exists between the two [41]. Brynjolfsson & Hitt further expanded on the basis of their original research [43]. The new study found that an improvement in the degree of informatization not only helps to improve the total factor productivity, but also helps the country's economic growth [43]. Jorgenson Ho & Stiroh found that information technology has a stimulating effect on economic growth, but only in a specific period of time [44]. In addition to the United States, the link between economic development and industrial intelligence in developing countries has also been the focus of research. Gholami, Moshiri & Lee used Iran's six-year manufacturing industry data, from 1993 to 1999, to prove that information and communications technology (ICT) can help improve total factor productivity, thereby promoting economic development [45]. Hawash & Lang used four years of data from 33 developing countries as a research sample [46]. The study found that, compared with developed countries, information technology can play a better role in promoting manufacturing in developing countries, as well as promoting manufacturing and business upgrades in developing countries [46].

As the level of industrial intelligence has continued to improve, especially with regard to the application of artificial intelligence technology in industry, the academic community has begun to shift the focus of research to the relationship between industrial intelligence and total factor productivity. Some research results have shown that industrial intelligence can effectively promote an improvement in manufacturing total factor productivity [47]. Graetz & Michaels used industrial robots in 17 countries and regions as samples [48].

Empirical tests found that the use of robots can improve total factor productivity, but the increase in labor productivity was limited to only 0.36% [48]. Acemoglu & Restrepo argued that industrial automation can increase productivity by replacing labor with relatively cheap capital [49]. Papagiannidis and Marikyan found through their study on the use of smart offices in production that the total factor productivity of companies was significantly improved after the application of smart office devices [50]. Wu et al., on the other hand, found that modern smart technology, represented by internet technology, has become an important factor in China's total factor improvement after an empirical study of production data from 2006–2017 across Chinese provinces [51]. In addition the study found that smart technologies not only enhance total factor productivity in the region, but also have a positive impact on the surrounding areas. Li et al., on the other hand, conducted a study on listed manufacturing firms in China, and their findings suggest that the application of smart technologies and the implementation of stable economic policies will help improve the total factor productivity of firms [52]. Jiang et al. found that the total factor productivity of manufacturing firms applying smart technologies was much higher than the industry average [53]. The application of smart technologies effectively reduced production costs and expanded financing channels, which in turn led to an increase in the total factor labour productivity of the firms [53]. Kromann et al. analyzed the manufacturing data of nine countries and concluded that the use of industrial robots can effectively improve total factor productivity [54].

Conversely, some studies have maintained that industrial intelligence will inhibit total factor productivity. Brynjolfsson et al. found that the rapid development of industrial intelligence did not bring about an increase in productivity, but caused a significant decline; there was, in reality, a "productivity paradox" [55]. Acemoglu & Restrepo believed that the "abuse" of automation leads to a waste of resources and the inability of the labor force to match the artificial intelligence technology [49]. The study maintained that these are the key factors inhibiting the improvement of total factor productivity [49]. Gordon conducted a study on the development of the manufacturing industry in the United States over the past decade [56]. The results revealed that, although the technological innovation capability of the United States has been accelerating in the past decade, the productivity performance has slowed down year-by-year [56]. The reason for this finding may be that the success of the information technology (IT) revolution failed to affect the manufacturing industry. Rather, IT benefits consumers more, leading to a significant bias in the estimates of total factor productivity [56].

The third and final aspect is the study of the relationship between industrial intelligence and population structure. Early research focused on the study of industrial intelligence and labour substitution. For example, Pajarinen & Rouvinen believed that artificial intelligence technology can replace labor [57]. Frey used the machine learning method to predict that half of the more than 700 occupations in the United States will be replaced by artificial intelligence in the short term [58]. This could lead to social problems, such as unemployment [58]. However, Dauth et al., through a study of German companies, found that artificial intelligence did not affect employment [59]. Manyika et al. showed that people have positive attitudes towards the replacement of labour by artificial intelligence, but the improvement of the social security system for the replaced population should be fully considered in the formulation of actual industrial policies [15]. Smith and Waldeau argue that although AI technology has come a long way, it is not a complete replacement for human labour at this stage, and that the application of AI technology is mainly to help workers with difficult tasks [60]. Tschang & Almirall study the impact of industrial intelligence applications on employment and analyse it in the context of artificial intelligence substitution cases, finding that industrial intelligence applications will gradually replace workers in low-skilled labour, but will also generate new demand for highly skilled labour [61]. Mutascu, through an analysis of production data for 23 developed countries from 1998–2016, finds that the application of AI technology will help reduce unemployment only at low inflation levels [62]. In other cases, AI did not show a significant correlation with the unemployment rate [62].

Current research focuses on the link between industrial intelligence and population aging. Clauberg argues that the application of AI technologies in production is more desirable in developed countries with a high level of population ageing compared to developing countries with a large population [63]. Abeliansky & Prettner believed that, for every 1% decrease in the population growth rate in countries with a higher concentration of aging populations, the installed density of robots will increase by nearly 2% [64]. Acemoglu & Restrepo tested the relationship between aging and artificial intelligence technology by constructing a theoretical model [65]. The results showed that an aging population will stimulate the development and application of artificial intelligence technology, and then promote the economic growth of a country or region [65]. Following the same line of reasoning, Acemoglu & Restrepo empirical analysis of 722 commuting areas in the United States also found that areas with a higher degree of aging have a correspondingly larger number of robot integration companies [49]. This positive association is particularly pronounced in industries that are highly-dependent on the middle-aged (24–55) labor force [49]. Ruiz-Real's research shows that industrial intelligence based on artificial intelligence technology can effectively address the threats to agricultural production arising from an ageing population. By upgrading agricultural intelligence, it will help to alleviate labour supply pressure and improve agricultural production efficiency [66]. Abuselidze & Lela show that the increasing ageing of the population will facilitate the development of industrial intelligence [67]. In addition, the low-skilled workers displaced by industrial intelligence will be able to work in service industries such as social security, providing a wider range of social services for the ageing population [67]. Nazareno & Schiff based their analysis on comprehensive social survey data for 402 industries from 2002–2008. In developed countries with a high level of ageing, it is difficult to replace their workforce by AI technology, as their manufacturing industries tend to produce mainly higher technology products, and the application of industry intelligence technologies such as AI technology can lead to a rapid increase in the cost of products [68].

2.2. Literature Summary

The academic literature on population ageing, the economic benefits of industrial intelligence and the link between industrial intelligence and population ageing provides an important reference for this study. By reading the existing literature, it can be seen that there are several shortcomings in the existing studies: firstly, there are more studies on the impact of population ageing on the development of manufacturing industries and on export trade, but there are fewer studies on the topic of the impact of population ageing on the technical complexity of exports, especially manufacturing exports. Secondly, the link between industrial intelligence and demographics and its impact on economic development has been studied from different perspectives in the literature, but at this stage there are relatively few studies that combine population ageing, industrial intelligence and export technological sophistication.

For these reasons, this paper will explore the intrinsic links between population ageing, industrial intelligence and export technological sophistication, and attempt to expand on them in two ways: first, by constructing an empirical model using cross-country-level and industry-level data, and by theoretically elaborating and empirically testing the association between the degree of population ageing and export technological sophistication in 43 countries around the world. Secondly, industrial intelligence is incorporated into the analytical framework to further investigate the mechanism of the impact of population ageing and industrial intelligence on the technological complexity of exports.

3. Theoretical Mechanisms and Research Assumptions

3.1. Theoretical Foundations and Institutional Pathways

Leontief's new factor theory of international trade argues that, in addition to land, labour and capital, technology, human capital, research and development, information and management should all be added to international trade as factors of production and play a decisive role in a country's comparative advantage in international trade. Among other things, the human capital and technology referred to in the theory are relevant to this study.

In terms of human capital, Schults' human capital theory states that human capital is a type of capital embodied in workers, expressed as the sum of the quantity and quality of workers, i.e., the value of their knowledge, skill level, work capacity and health status, and that the level of a country's human capital will also determine the level of its comparative advantage in participating in the international division of labour [69].

In terms of technology, the growth mode proposed by Solow has successfully demonstrated that technological progress leads to a change in the production function without an increase in other factors of production inputs, which in turn leads to long-term economic growth, and therefore technological progress is considered to be one of the main driving forces of economic growth and the enhancement of a country's comparative advantage in international trade [70].

Based on the above theory and in the context of the research, the following mechanism of action is proposed (Figure 1) and elaborated later in the paper.

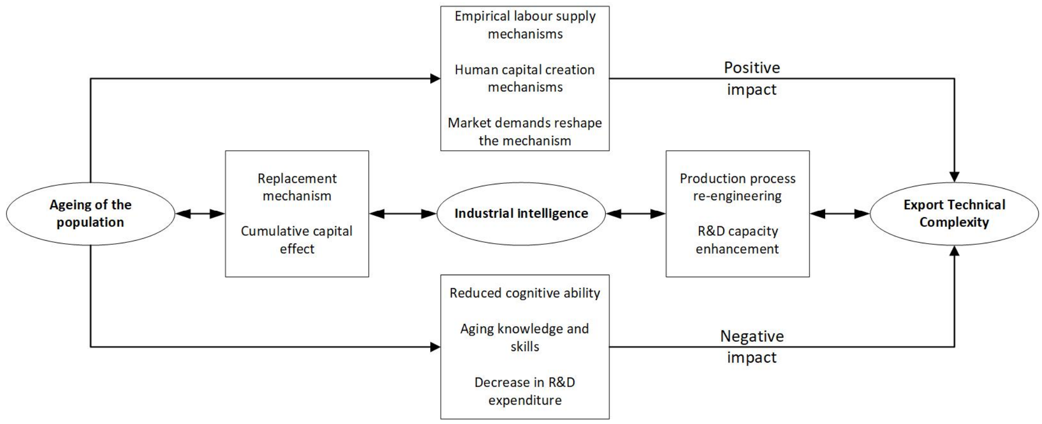

Figure 1. Mechanism of the role of population ageing, industrial intelligence and technological complexity of exports.

3.2. The Impact of Population Aging on the Technological Complexity of Exports

Based on Schults' human capital theory [69], this paper argues that there are two opposing mechanisms of influence in the study of the impact of population ageing on export technological sophistication: a positive influence, whereby an ageing age structure contributes to an increase in export technological sophistication, and a negative influence, whereby an economy's export technological sophistication is hindered as its age structure ages.

3.2.1. Positive Impact

(1) Experiential labour supply mechanisms. In 1962, Arrow put forward the concept of "learning by doing" [71], pointing out that, by trying to solve the problems arising in labor production, the production efficiency of laborers will also be improved. An increase in the proportion of the elderly in the overall population will increase the proportion of skilled labor, thereby contributing to an increase in the technological sophistication of exports. Crouch believes that labor efficiency is determined by variable intelligence, fixed intelligence and physical fitness [72]. Among them, fixed intelligence is composed of work and life experience; therefore, fixed intelligence will gradually increase with age [72].

Hence, older workers have more advantages in industries with higher technical complexity, such as high-precision manufacturing, and these workers can have a positive impact on the technical complexity of exports [72]. Backes-Gellner et al. pointed out that, in the same production environment, older workers can help younger workers improve their technical level and personal ability by guiding and teaching [73]. Through this approach, aging can also promote the export of technical complexity to a certain extent.

(2) Human capital creation mechanisms. Human capital is also one of the important factors that affect the technical complexity of exports; the aging of the population helps to improve the level of human capital, to a certain extent. Disney & Richard pointed out that aging workers offer a mature labor force and rich work experience, which will save enterprises labor costs and improve labor efficiency [74]. On the other hand, although the intensification of the degree of aging has reduced the total labor supply, laborers' wages have increased. Higher wages increase people's confidence in the expected benefits of education, prompting people to be more willing to invest in education. This is conducive to the improvement of human capital levels [74]. This same view is also supported by the findings of Sadahiro & Shimasawa, which showed that, as the proportion of young people in the population declines, the future benefits of education motivate young people to devote more time to human capital investment [75]. This, in turn will improve the labor force's own skill level while offsetting the adverse impact on the labor force caused by population decline [75].

(3) Market demands reshape the mechanism. An ageing population will inevitably lead to a change in the structure of market demand, which in turn will trigger an upgrade in the industrial structure. With the continuous growth of the social dependency ratio of the elderly, the demand for high-tech industries such as health, pension, and insurance also increases. In addition, countries with an aging population have greater demand for high-tech industries. Gehringer & Prettner pointed out that an aging population means an increase in life expectancy, and people will increase their savings to maintain their consumption levels after retirement [76]. The increase in the accumulation of physical capital will reduce the real interest rate, save on the cost of R&D financing, increase the level of R&D investment, and promote the investment demand for high-tech services and manufacturing [76]. In addition, the technical complexity of exports will be increased through the effect of demand preference [76].

3.2.2. Negative Impact

The cognitive abilities of the elderly gradually decline with age. According to the analysis of Verhaeghen & Salthouse, after reaching a certain age, the abilities of human memory and logical reasoning will show a more obvious downward trend [77]. Backes-Gellner et al. investigated the changing trends of physical fitness and variable intelligence with age [73]. The study found that physical fitness and variable intelligence show an inverted U-shaped trend with age [73]. That is, after reaching a certain age, physical fitness and variable intelligence will decline in line with age. The decline of variable intelligence and physical fitness is not conducive to the improvement of export technical complexity.

The aging knowledge structure of the elderly population is also not conducive to technological development. With the rapid iteration of science and technology, the knowledge stock of individuals will gradually fail to keep up with the development of the times. If knowledge is not updated and supplemented, people's knowledge structure will tend to age, which in turn will hinder technological progress. The aging of society as a whole will hinder the technological sophistication of exports.

An aging population will lead to a reduction in society's R&D spending. The weakening of the demographic dividend and the intensification of the aging population has led to a rapid increase in the country's social security spending. In response to this problem, the government, on the one hand, increases fiscal revenue by increasing corporate tax burdens. The increased tax burden will lead to a reduction in corporate R&D spending. On the other hand, the government will reduce some non-essential expenditure, including on R&D. All of these measures will adversely affect innovation activities, which in turn will affect the technological complexity of exports.

Based on the above content, this paper proposes the following hypotheses:

Hypothesis 1a. *Population aging has a significant positive impact on the technical complexity of a country's (region's) exports.*

Hypothesis 1b. *Population aging has a significant negative impact on the technological complexity of a country's (region's) exports.*

3.3. The Mediating Effect of Industrial Intelligence

According to the Solow growth mode [70], this paper argues that the increasing ageing of the population is reducing the supply of labour as a factor of production, and that an intelligent transformation of the manufacturing industry is inevitable in order to ensure productivity and the development of the national economy. At the same time, the intelligent transformation of the industry has contributed to the reshaping of the industrial structure of the manufacturing industry and the improvement of research and development capabilities, which in turn has contributed to the increase in the technological complexity of manufacturing exports.

Based on the above analysis, this paper proposes that in the context of an ageing population, the following mechanisms exist for the main impact of industrial intelligence on the technological complexity of exports.

(1) A complementary replacement mechanism for industrial intelligence. The dwindling supply of labour due to ageing is a direct driver of industrial intelligence [13]. A reduction in the scale of labour supply inevitably leads to higher labour demand, higher labour market prices and higher labour cost expenditure for enterprises. In order to reduce the labour cost expenditure of enterprises and increase the profit per unit of labour production, industrial intelligence has come into being. The application of artificial intelligence technology in industrial intelligence will help to reduce the demand for labour in the production process, thereby mitigating the negative impact of insufficient labour supply on the production of enterprises.

Compared to traditional mechanical automation, artificial intelligence technology enables further automation of production processes through big data, intelligence, cloud computing and other technologies, and generates a more substantial replacement of labour, thereby reducing the demand for low-skilled labour. However, it is worth noting that AI acts as a complementary replacement for labour, with experienced labour more able to take advantage in the age of industrial intelligence. Research by Acemoglu and Restrepo using US labour market data suggests that the use of a new robot in the US would reduce employment by 3–5.6 workers [49]. Chui et al. further predicted that if AI systems could perform at a moderate level of human performance, then 58% of jobs in the US could be performed using AI systems [78]. The results of the empirical analysis by Autor and Salomons suggest that productivity gains from industry intelligence reduce the contribution of labour to industry growth, thereby reducing the dependence of the market on labour [79].

(2) The cumulative capital effect of industrial intelligence. Traditional life-cycle theory suggests that the higher the proportion of a country's total population that is in the labour force, the higher the level of savings and investment in that country. Conversely, countries with a higher proportion of older people have a lower ratio of savings to investment. At the same time, the reduction in labour supply due to an ageing population will lead to diminishing marginal output of capital, which in turn will reduce the rate of return on investment, and the investment and savings rates will then move downwards. Japan, a country with a high level of ageing, has seen its investment rate fall from 40.9% in 1970 to 22.96% in 2010–2016, according to WDI statistics [80].

Artificial intelligence, on the other hand, will increase the rate of return on capital, thus raising the savings and investment rates and weakening the impact of ageing on capital accumulation. Chen argues that as the level of artificial intelligence increases, the level of intelligence and automation in the production process will continue to increase and more and more production tasks can be performed with capital instead of labour, thus making capital more important than labour in the production process and increasing the rate of return on investment as a result [81]. As Aghion et al. show the application of AI will facilitate the acceleration of the automation process while increasing productivity [82]. This will lead to a reduction in the use of human labour in the production process, allowing for an increase in the share of capital returns in the economy.

(3) The infiltration and expansion effect of industrial intelligence. The impact of industrial intelligence on the technological complexity of exports is achieved in two main ways: firstly, by reshaping the production and manufacturing chain through the play of intelligent infiltration effects; secondly, by promoting the improvement of product development capabilities through border expansion effects.

In terms of promoting the re-engineering and re-upgrading of manufacturing processes, artificial intelligence directly affects all aspects of the manufacturing process and promotes the intelligent upgrading of production processes. The development of the integration of artificial intelligence and manufacturing will contribute to the intelligence of the production process and the intelligence of the manufacturing process of the enterprise. The use of big data and cross-disciplinary intelligence will reduce the cost of innovation and optimise a company's responsiveness to market information. In processing and manufacturing, the application of artificial intelligence technology can complete complex collaborative processes, reduce labour costs and increase the technological added value of intermediate manufacturing processes. Graetz and Michaels argue that the application of AI in manufacturing is actually a process of capital replacing labour, thus bringing about fundamental changes to the production process and significantly increasing labour productivity [36]. Through the above analysis, the application of industrial intelligence in manufacturing processes will contribute to an increase in the technological complexity of exports.

Industrial intelligence can facilitate the improvement of industrial R&D capabilities. The application of industrial intelligence can design the best product solutions by saving time on exploration and experimentation in R&D, and quickly introduce brand new products to the market through production process intensification. Paul et al. found through a study on the application of artificial intelligence technology in the biopharmaceutical industry that the application of artificial intelligence can provide faster design and optimisation of drug structures, shortening the time consumption [83]. This shows that intelligence in product development can accelerate product innovation and increase the complexity of export technology.

Therefore, based on the above analysis, this paper proposes:

Hypothesis 2. *Industrial intelligence plays a mediating effect on the impact of population aging on the technological complexity of high-tech exports.*

4. Research Design

4.1. Data Sources

In order to measure the research variables used here, the data in this paper mainly come from four sources. First, the 2016 version of the World Input-Output Database (WIOD) is used to calculate the technical complexity of the exports of 16 manufacturing industries in 43 countries, from 2000 to 2014 [84]. Second, referring to Acemoglu [49], this paper uses industrial robot data collected by the International Federation of Robotics (IFR) to measure the intelligence of the manufacturing sector, using data on industrial robots containing annual installations and stocks of robots in 16 manufacturing industries in 73 countries for the period 1993 to 2020.Third, this paper controls the variables that affect the technical complexity of exports at the industry level in each country. The measurement data of these variables come from the WIOD's Socio-Economic Accounts (SEA). The SEA contain the data of added value, employment population, capital stock and other data of different industries in major countries. Fourth, data pertaining to other country-level control variables for export technological complexity come from the World Bank database. After matching the data with the industrial robot data, the research samples of 16 manufacturing industries in 43 countries, from 2000 to 2014, were obtained. After removing some missing value samples, the actual research sample size was 10,294.

4.2. Variable Description

The research variables in this paper include explained variables (export technical complexity), core explanatory variables (industrial intelligence and population aging) and a series of control variables. Next, a brief description of the measurement of these main research variables is given.

4.2.1. Measurement of Export Technical Complexity

Based on the decomposition framework of export value added by Wang et al. [85], and with the help of the 2016 version of the WIOD, this paper decomposes the export value added of each country's manufacturing sub-sectors from the perspective of backward correlation. Then, according to Equations (1) and (2), the export technical complexity of each country's manufacturing sub-sectors, from 2000 to 2014, is calculated. The technical complexity of an industry's exports can reflect a country's position in the global value chain, to a certain extent. The higher the technical complexity of a country's exports is, the higher the position in the global value chain that country will be.

$$TS_j = \sum\nolimits_j \frac{VX_{ji}}{\sum_j VX_{ji}} NPRODY_j \tag{1}$$

$$NPRODY_j = \sum\nolimits_i \frac{VX_{ji}/\sum_j VX_{ji}}{\sum_i {}^{VX_{ji}}/\sum_j VX_{ji}} Y_i \tag{2}$$

In Equations (1) and (2), vx_{ji} represents the added value of exports of industry j in country i; Y_i is the per capita GDP of country i after purchasing power parity, and $NEXPY_j$ represents the export technical complexity of the industry. The larger the value is, the higher is the export technical complexity. In the empirical study, the calculated value of export technical complexity takes the natural logarithm.

4.2.2. Measure of Industrial Intelligence

Existing literature mainly measures the degree of intelligence of an industry according to the application of robots in the industry, e.g., the study of Acemoglu and Restrepo [86]. Referring to Acemoglu's research, this paper uses robot usage density as a proxy variable for the degree of industrial intelligence, where robot usage density refers to the number of robots in the industry per thousand employed people. The greater the use density of robots is, the higher is the level of industrial intelligence. Using the robot data provided by the International Federation of Robotics, and the employment population data contained in the WIOD socioeconomic account, this paper calculates the number of robots owned by each country's manufacturing sub-sector per thousand employed population by year. Industrial intelligence is represented by I-AI in the diagram.

4.2.3. Measure of Population Aging

The aging degree of a country's population can be measured by the proportion of the elderly population in the total population. This is generally either the proportion of the population aged 60 and over in the total population, or the proportion of the population aged 65 and over in the total population. This paper directly uses the proportion of the population aged 65 and over to the total population, as published by the World Bank database, to measure the degree of population aging in each country. The ageing of the population is indicated in the table by Old.

4.2.4. Measures of Control Variables

Considering that the omission of important explanatory variables may cause biased estimation results, combined with existing literature research, this paper adds the following control variables:

(1) Manufacturing capital stock per capita (CSC). The labor capital stock reflects the investment level of the industry, and affects the industry's position in the global value chain by affecting the investment in machinery and equipment, so this paper controls CSC. The measurement method adopts the proportion of manufacturing employment population to the total capital stock, and takes the natural logarithm in the empirical study.

(2) Foreign direct investment (FDI). A large amount of FDI provides the necessary funds for the development of the manufacturing industry, and also brings advanced technology and management experience. This greatly promotes the economic development of a country or region, which in turn contributes to the export of technological complexity improvement. In the measurement of this variable, the traditional calculation method in the academic circle is adopted; that is, the proportion of the actual utilization of foreign capital in the current year to the regional GDP is expressed.

(3) Internet development level (Internet). Some studies have shown that Internet development has promoted the improvement of export technology complexity through both the information cost saving effect and the human capital improvement effect. Therefore, this paper controls the Internet development level of each country and uses the proportion of Internet population to the total population as a measure.

(4) Human capital (HC). Considering that human capital can affect the technical complexity of exports through two ways, namely flow and stock, this paper controls HC and uses the change in human capital from 2000 to 2014, as reported in the Penn World Table, to represent HC.

In addition, referring to Hausmann's research on the factors that affect the technical complexity of service exports [23], this paper also controls the size of the manufacturing employment population and the level of economic development in each country. The scale of manufacturing employment is measured by the proportion of manufacturing employment to total employment. The level of economic development is measured by the natural logarithm of per capita GDP, and the per capita GDP is measured in 2010 constant US dollars. The above data are sourced from the World Bank database [87].

4.3. Empirical Model Building

This paper first empirically tests the impact of population aging on the technical complexity of exports by using the cross-country data of manufacturing. An empirical model is constructed, as shown in Equation (3).

$$TS_{jit} = \alpha_0 + \alpha_1 Old_{jit} + \beta IND_{jit} + \gamma CTR_{jit} + \delta_j + \theta_i + \varphi_t + \varepsilon_{jit} \tag{3}$$

In Formula (3), jit represents the manufacturing sub-sector, country, and year, respectively; TS is the technical complexity of manufacturing exports; 'Old' represents the degree of aging; IND represents the industry-level control variable, including a variable of capital stock; CTR represents the country-level control variable, including the use of foreign direct investment, the proportion of the Internet population, the proportion of manufacturing employment, and the level of economic development. Next, δ, θ, and φ represent industry fixed effects, country fixed effects, and year fixed effects, respectively; ε represents a random error term; α_1 is the estimated coefficient upon which this paper focuses. If α_1 is significantly positive, this means that industrial intelligence can significantly promote the improvement of export technology complexity.

This paper draws on the causal steps approach proposed by Baron and Kenny [43]. Also, the mediation effect model is used to further test whether there is a channel through which population aging affects the technical complexity of exports through industrial intelligence. The specific model is as follows:

$$TS_{jit} = \alpha_0 + \alpha_1 Old_{jit} + \alpha_2 IND_{jit} + \alpha_3 CTR_{jit} + \delta_j + \theta_i + \varphi_t + \varepsilon_{jit} \quad (4)$$

$$AI_{jit} = \beta_0 + \beta_1 Old_{jit} + \beta_2 IND_{jit} + \beta_3 CTR_{jit} + \delta_j + \theta_i + \varphi_t + \varepsilon_{jit} \quad (5)$$

$$TS_{jit} = \lambda_0 + \lambda_1 Old_{jit} + \lambda_2 AI_{jit} + \lambda_3 IND_{jit} + \lambda_4 CTR_{jit} + \delta_j + \theta_i + \varphi_t + \varepsilon_{jit} \quad (6)$$

In the above model, AI_{jit} is an intermediary variable, which refers to industrial intelligence; the definitions of other variables remain unchanged.

This paper adopts the step-by-step test method; the inspection steps are as follows: first, the coefficient α_1 of Model (4) is inspected. If coefficient α_1 is significant, then coefficient β_1 of Equation (5) and the λ_2 of Equation (6) are inspected in turn. If α_1, β_1 and λ_2 are all significant, the mediating effect is significant. At this time, if λ_1 in Equation (6) is not significant, that is, if the direct effect is not significant, λ_1 is a complete mediation effect; if λ_1 is significant, the direct effect is significant, and the result is a partial mediation. If at least one of β_1 and λ_2 is not significant, then continue to use the Sobel test to further determine whether there is a mediating effect.

5. Empirical Results and Analysis

5.1. Basic Regression Results

In order to accurately examine the impact of population aging and various control variables on the technical complexity of manufacturing exports, and following the principle of "from general to special" [88], the explained variables and the core explanatory variables are first regressed separately. Then, the control variables are added in turn. The specific regression results are shown in Table 1 below.

Table 1. Basic regression results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Old	1.005	3.838 **	3.760 **	3.739 **	3.691 **	3.561 **	4.940 ***
	(1.885)	(1.766)	(1.771)	(1.762)	(1.764)	(1.778)	(1.817)
CSC		0.359 ***	0.359 ***	0.329 ***	0.328 ***	0.329 ***	0.330 ***
		(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
FDI			–0.012	0.022	0.021	0.022	0.019
			(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
PGDP				1.100 ***	1.101 ***	1.119 ***	0.776 ***
				(0.119)	(0.120)	(0.123)	(0.165)
Internet					–0.073	–0.040	0.203
					(0.154)	(0.159)	(0.169)
HC						–0.224	–0.300
						(0.215)	(0.217)
Labor							0.027 ***
							(0.009)
_cons	6.141 ***	4.111 ***	4.122 ***	–7.489 ***	–7.492 ***	–6.935 ***	–3.897 **
	(0.237)	(0.243)	(0.243)	(1.271)	(1.272)	(1.329)	(1.655)
N	12,678.000	10,024.000	9992.000	9992.000	9941.000	9924.000	9924.000
r2	0.510	0.638	0.639	0.643	0.643	0.644	0.644
ar2							
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are in parentheses; ** $p < 0.05$, and *** $p < 0.01$.

The regression results show that, after adding control variables step-by-step, the coefficient of 'Old' is significantly positive at the 1% level. The core explanatory variable parameter estimation results are relatively robust. This finding indicates that the aging rate significantly and positively affects the technical complexity of manufacturing exports, improving the division of labor in the world value chain of a country or region and the competitiveness of its industries. Thus, Hypothesis 1a is verified.

The per capita capital stock of manufacturing employees was significantly positive during the sample inspection period, and an increase of per capita capital stock can significantly improve the rate of technological progress. Improving the rate of technological progress will have a positive impact on the technical complexity of exports. The estimated coefficient of foreign direct investment is not significant. This finding indicates that, with the continuous development of a country or region's manufacturing industry, improving the technical complexity of manufacturing exports cannot rely on international capital and undertaking international industrial transfers. Relying only on external investment may restrict developed countries to the low-end link of the global value chain due to such countries' weak manufacturing background. This approach is not conducive to the upgrading of the manufacturing value chain of a country or region. A significantly positive coefficient of per capita GDP indicates that the more developed the economic level of a country or region is, the more frequent its R&D activities will be, the faster the development of high-tech manufacturing will be, and the more positive will be the likelihood that the country or region can promote the technical complexity of manufacturing exports. The estimated coefficient of Internet development level is not significant. Some studies have shown that the development of the Internet can effectively promote the improvement of export technology complexity. However, due to the large division of labor among Internet users, and the uneven quality of the users themselves, even though a large number of people are using the Internet, the Internet itself has not had a significant impact on the technical complexity of exports. The estimated coefficient of human capital level is not significant. This finding indicates that, although a country or region has a huge pool of human resources, the contradiction in human capital structure between high-end R&D and a shortage of skilled talents has become an important constraint on manufacturing innovation and export technology complexity. The estimated coefficient of manufacturing employment is significantly positive. A huge manufacturing population is conducive to the supply of the manufacturing talent market and provides important labor support for enterprises to improve export quality.

5.2. Mediating Effect Analysis

Based on the results of the basic regression analysis in the previous section, it can be seen that population ageing can, to some extent, have a positive impact on export technological sophistication. On this basis, this study argues that industrial intelligence plays a mediating effect between population ageing and export technological sophistication, based on the boosting effect of technological progress on international trade advantage in the Solow growth mode Therefore, Hypothesis 2 will be further tested empirically in this paper through a mediating effects model.

Table 2 shows the regression results with industrial intelligence as the mediating variable. Column (2) shows that the regression coefficient of population ageing on industrial intelligence is significantly positive at the 1% level, and column (3) shows that the coefficients of Old and I-AI are significantly positive at both the 5% and 1% levels, with the mediating effect accounting for 16.59% of the total effect, thus verifying that population ageing can influence export technological sophistication through industrial intelligence.

Combining the previous theories on population ageing, industrial intelligence and technological complexity of exports, it can be seen that industrial intelligence can cope with the impact of increasing ageing rates on manufacturing. It has restructured the labour supply to improve the efficiency of technological innovation and attenuate the adverse effects of an ageing population on capital. Realising the compensatory substitution effect of industrial intelligence and an ageing population to achieve total factor upgrading, thus having a positive impact on the technological sophistication of exports.

Worth noting is that the proportion of the population using the Internet has significantly promoted the increase in the technical complexity of exports. Due to the improvement in the degree of industrial intelligence, the integration and development of Internet technology and manufacturing have continued to deepen. Therefore, in the process of promoting the intelligentization of the manufacturing industry, the powerful role of the Internet's development has emerged. Internet technology can provide impetus for the development of the manufacturing industry, which in turn is conducive to improving the technical complexity of exports.

Table 2. Mediating effect estimates (1).

	(2)	**(3)**
	Industrial intelligence	Export technical complexity
Old	97.879 **	3.937 **
	(45.137)	(1.961)
I-AI		0.008 ***
		(0.001)
CSC	1.830 ***	0.343 ***
	(0.218)	(0.020)
FDI	–0.125	0.038
	(0.327)	(0.046)
PGDP	–9.875 ***	0.774 ***
	(2.369)	(0.178)
Internet	–8.925 ***	0.312 *
	(2.700)	(0.180)
HC	–1.910	–0.248
	(3.486)	(0.225)
Labor	–0.029	0.034 ***
	(0.129)	(0.010)
_cons	90.485 ***	–4.176 **
	(27.716)	(1.801)
N	7847.000	7595.000
r2	0.372	0.667
ar2		
Industry	Yes	Yes
Year	Yes	Yes
Country	Yes	Yes

Notes: Standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3. Tests of Heterogeneity

The basic regression results examine the impact of population ageing on the technological complexity of exports from a global perspective, as well as the impact of industrial intelligence as a mediating variable on the technological complexity of exports. However, the technical level and industry characteristics of different manufacturing industries are different; the economic level of each country or region is also uneven. As a result, the impact of population aging on the technical complexity of exports in different industries and regions is also different. Therefore, this paper conducts a heterogeneity analysis from three aspects: industry type, region type and population structure.

5.3.1. Industry

This paper divides the overall sample into two samples: high-tech industry and low-tech industry. The 15 industries involved were divided with reference to the research of Zhang & Jiang [89]. High-tech industries include electrical machinery and equipment, ferrous metal smelting and rolling, chemical fibers, chemical raw materials and chemical products, computer communications, other electronic equipment, metal products, automobiles, petroleum processing, coking and nuclear fuel, railways, ships, aviation, other transportation equipment, general equipment, rubber and plastic products, tobacco products, medicine, instrumentation, non-ferrous metal smelting and calendering, and special equipment. The rest of the industry is low-skilled, mainly manual labour.

Table 3 reports the specific effects of population ageing on the technological complexity of exports through industrial intelligence in different technology types of industries. Compared to the regression with the benchmark, the results of the industry heterogeneity analysis show the following characteristics. The ageing of the population has had a positive effect on the technological complexity of exports from high technology industries and has not had an effect on low technology industries. This finding is consistent with the experienced labour supply mechanism mentioned earlier, whereby the older population is better able to exploit the value of their experience in higher-skilled industries and increase the technological content of their exports. The introduction of industrial intelligence, on the other hand, has led to an increase in the technological sophistication of exports from low-tech industries, a finding that is consistent with the complementary substitution mechanism proposed in this paper. That is, the intelligent transformation of industry addresses the shortage of low-skilled labour due to ageing on the one hand, while creating new types of jobs available to the experienced workforce and, in doing so, increasing the technological sophistication of exports.

Table 3. Industry Heterogeneity.

	HighTECH	**LowTECH**
Old	3.552 **	4.193
	(2.280)	(3.329)
I-AI	0.004 ***	0.007 *
	(0.001)	(0.004)
CSC	0.332 ***	0.167 ***
	(0.025)	(0.034)
FDI	0.031	0.054
	(0.061)	(0.079)
PGDP	0.879 ***	0.918 ***
	(0.218)	(0.296)
Internet	0.171	0.352
	(0.203)	(0.330)
HC	–0.201	–0.347
	(0.275)	(0.292)
Labor	0.035 ***	0.032 **
	(0.013)	(0.014)
_cons	–5.997 ***	–4.947 *
	(2.173)	(2.949)
N	4855.000	2192.000
r2	0.722	0.672
ar2		
Industry	Yes	Yes
Year	Yes	Yes
Country	Yes	Yes

Notes: Standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

5.3.2. Country

This article divides 43 countries and regions according to the median per capita GDP in 2014, which is used as the dividing line. Countries with per capita GDP above the median are classified as high-income countries; countries with per capita GDP below the median are classified as low-income countries. The regression results are shown in Table 4.

Table 4, which distinguishes between the 43 countries, visualises that the estimated coefficient on population ageing is significant in high-income countries, indicating a positive push, and insignificant in low-income countries. The reason for this is that high-income countries are mainly developed Western countries such as the United States, the United Kingdom and Japan, which tend to be at the upper end of the manufacturing value chain and are more dependent on technology, i.e., there is a greater demand for experienced labour. Low-income countries, on the other hand, are dominated by countries in regions such as South East Asia and South America. The low-end manufacturing sector is more valued by low-income countries and is therefore less dependent on technology and more in need of a manual workforce.

Table 4. Country heterogeneity.

	(1)	(2)
	High Income	Low Income
Old	4.733 **	3.749
	(2.042)	(6.977)
I-AI	0.007 ***	0.074 **
	(0.001)	(0.034)
CSC	0.467 ***	0.130 ***
	(0.029)	(0.028)
FDI	0.016	0.430
	(0.044)	(0.587)
PGDP	0.050	1.581 ***
	(0.254)	(0.382)
Internet	0.049	−0.002
	(0.203)	(0.428)
HC	0.460	−0.783 **
	(0.308)	(0.361)
Labor	0.053 ***	−0.001
	(0.012)	(0.020)
_cons	0.210	−7.803 **
	(2.470)	(3.084)
N	5612.000	1983.000
r2	0.539	0.662
ar2		
Industry	Yes	Yes
Year	Yes	Yes
Country	Yes	Yes

Notes: Standard errors are in parentheses; ** $p < 0.05$, and *** $p < 0.01$.

In addition, the introduction of industrial intelligence has had a positive effect on the technological sophistication of exports from developed countries, and has also contributed to the technological sophistication of exports from less developed regions. According to the human capital creation mechanism proposed in this paper, the advantages of human capital creation are more pronounced in high-income countries. An increase in human capital will contribute to an increase in the level of education of the workforce, which in turn will allow the country to produce more technologically advanced products. At the same time, the introduction of industrial intelligence has dampened the negative effects of an ageing population on capital, promoted capital accumulation and raised the technological complexity of exports. In line with the analysis of low-skilled industries, for low-income countries the complementary substitution effect of industrial intelligence successfully complements the manual labour deficit. At the same time, industrial intelligence as a new development model also helps low-income countries to transform intelligently and to a certain extent optimise and transform their industries. Thus, industrial intelligence plays a crucial role in increasing the technological sophistication of the exports of low-income countries.

5.3.3. Aging Population

On the basis of the benchmark regression results, this paper adopts the method of age group division used in the United Nations data census. The elderly population data used in this paper are further distinguished, with the age of 70 set as the boundary. The proportion of the elderly population aged 60–70, and the elderly population over the age of 70 in the total elderly population, is used for classification.

The regression results (Table 5) show that the 60–70 age group contributes positively to the increase in technical complexity of exports, but the older population over 70 has no effect on the technical complexity of exports. Industrial intelligence, on the other hand, has an impact on the technological complexity of exports at all ages, and the findings are consistent with the impact path analysis in this paper.

Table 5. Aging population heterogeneity.

	(1)	**(2)**
	lncomplex	lncomplex
60–70	1.007 *	
	(0.568)	
71–100		0.658
		(0.583)
I-AI	0.008 ***	0.008 ***
	(0.001)	(0.001)
CSC	0.341 ***	0.340 ***
	(0.020)	(0.020)
FDI	0.039	0.035
	(0.046)	(0.046)
PGDP	0.831 ***	0.798 ***
	(0.175)	(0.177)
Internet	0.320 *	0.291
	(0.184)	(0.180)
HC	−0.223	−0.253
	(0.226)	(0.226)
Labor	0.031 ***	0.030 ***
	(0.010)	(0.010)
_cons	−4.680 **	−4.227 **
	(1.844)	(1.801)
N	7595.000	7595.000
r2	0.667	0.667
ar2		
Industry	Yes	Yes
Year	Yes	Yes
Country	Yes	Yes

Notes: Standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

5.4. Robustness Tests

5.4.1. Replace Explanatory Variables

Replacing the core explanatory variable population ageing degree measure for estimation, this paper uses the share of population aged 65+ in the total population for each country in the UN Population Outlook 2019 report as a proxy for the degree of ageing to verify the robustness of the paper's structure.

5.4.2. Add Omitted Variables

The position of the country in the GVC also plays a role in the technological complexity of exports, so this paper uses the position of the country in the GVC as a control variable for robustness testing.

5.4.3. Instrumental Variable

After the Haussmann test, the results show that the null hypothesis H0 is rejected; that is, "explaining variables are all exogenous variables". Therefore, there may be endogeneity problems caused by missing variables and other problems. In this paper, the instrumental variable (IV) is selected for endogeneity treatment. In this paper, the instrumental variable

(IV) hair was chosen for endogeneity treatment and the instrumental variable for the explanatory variable population ageing was identified as the average birth rate in every five-year period from April 1950 to April 1980, referring to Acemoglu et al. [90]. In regression using instrumental variables, the Cragg-Donald Wald F-statistic for identifying weak instrumental variables is greater than the 10% level critical value. At the same time, the Sargan statistic p-value of the over-identification test is greater than 0.05. This cannot reject the null hypothesis that all exogenous variables are not related to the random error term in the equation, indicating the validity and exogenousness of the instrumental variables.

5.4.4. Test Results

As can be seen, whether considering the endogeneity problem or replacing the explanatory variables, the degree of population aging still significantly increases the technical complexity of manufacturing exports. This result is basically consistent with the benchmark model, which in turn proves the robustness of the benchmark model results. Drawing on the research of Wang et al. [86], and using the instrumental variables in the benchmark model test, the instrumental variable method is used to test the endogeneity of the mediation effect model. The results in Table 6 are basically consistent with the results of the mediation effect model, which in turn verifies the mediation effect regression robustness of results.

Table 6. Mediating effect estimates.

	(1) Replace Explanatory Variables	**(2) Add Omitted Variables**	**(3) Instrumental Variable**
Old	5.426 ***	4.638 **	0.199 *
	(1.633)	(1.830)	(0.112)
CSC	0.330 ***	0.323 ***	0.326 ***
	(0.018)	(0.018)	(0.018)
GVC		0.708 ***	
		(0.234)	
FDI	0.023	0.017	0.021
	(0.038)	(0.038)	(0.039)
PGDP	0.810 ***	0.797 ***	0.854 ***
	(0.163)	(0.165)	(0.170)
Internet	0.155	0.203	0.097
	(0.169)	(0.169)	(0.174)
HC	−0.195	−0.306	−0.369 *
	(0.220)	(0.217)	(0.217)
Labor	0.027 ***	0.027 ***	0.021 **
	(0.009)	(0.009)	(0.009)
_cons	−4.241 **	−4.177 ***	−4.604 ***
	(1.655)	(1.652)	(1.673)
N	9924.000	9924.000	9839.000
r2	0.644	0.645	0.643
ar2			
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Country	Yes	Yes	Yes

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. Research Conclusions

This paper focuses on the relationship between population ageing and export and technological sophistication using panel data for 43 international and regional locations from 2000–2014, and the impact of population ageing on export technological sophistication through the mediating variable of industrial intelligence. The findings are as follows: Firstly, the paper proposes mechanisms for the impact of population ageing on the technological complexity of exports, namely the mechanisms of empirical labour supply, human capital creation and market demand reshaping. The empirical analysis concludes that population ageing contributes to some extent to the technological complexity of exports, which is in line with the findings of Gellner [73], Gehringer [76] and others. Secondly, this paper innovatively introduces the concept of industrial intelligence and examines its relationship with ageing and the technological complexity of exports. It was found that industrial intelligence, on the one hand, dampened the negative effects of an ageing population on the technological complexity of exports through a complementary substitution mechanism. On the other hand, the technological sophistication of exports is also facilitated by the cumulative effect of capital, intelligent infiltration and industrial reshaping. Finally, the paper distinguishes and examines these elements, considering that the technological content of the industry, differences in economic development and the age structure within the ageing population all have an impact on the technological complexity of the industry's exports. The findings suggest that an ageing population in high technology industries or in high income countries can significantly contribute to an increase in the technological complexity of exports. The reason for this is that this study argues that in the above division, the ageing population is able to exploit its experienced labour supply capacity and has led to an increase in human capital and an increase in the educational level of the workforce. The combination of experienced labour and highly qualified personnel has led to a significant increase in the technological content of export products. The introduction of industrial intelligence on the one hand further increases the technological complexity of exports from high technology industries or high-income countries. On the other hand, it increases the technological complexity of exports through the substitution of low-skilled labour and the reshaping of the industrial structure of low-income countries.

The findings of this paper contribute to a further understanding of the factors influencing export technological sophistication and have important theoretical and practical implications for how to accelerate the technological sophistication of manufacturing exports. The main policy implications are as follows.

First, countries and regions should properly understand the positive effects of population ageing. At present, population ageing has become a major trend in economic and social development, and its degree of development has an important impact on the economic development of a country (region). This paper uses fourteen years of data to verify that the current stage of population ageing has a catalytic effect on the increase in technological sophistication of manufacturing exports. And an increase in the technological complexity of exports will help countries or regions to improve their manufacturing competitiveness, improve their industrial structure and enhance their economic development. Therefore, countries and regions should make it a priority to play an active role for the ageing population when formulating policies related to ageing, such as promoting the employment or re-employment of the ageing population in highly skilled industries.

Secondly, the accumulation of human capital and the improvement of the quality of the workforce should be accelerated. Governments should promote equity in education so as to improve the overall quality of the workforce in less developed regions. Attract more foreign direct investment, especially in high-tech enterprises, by continuously strengthening its own economic strength. While improving infrastructure development, the focus is on developing the country's Internet level and forming an inclusive and virtuous development model with the manufacturing industry. It is also important to increase trade openness and enhance its own ability to digest and absorb advanced technology so that the technological sophistication of its manufacturing exports can be maximised.

Finally, countries and regions should vigorously promote the process of industrial intelligence in the face of ageing, enhance the level of industrial intelligence development, and consolidate the foundation and guarantee of manufacturing economic development. On the one hand, the negative effects of an ageing population are countered by increasing investment in and support for innovative and entrepreneurial activities, and by constantly improving the innovation and research and development capabilities of the manufacturing sector. On the other hand, we will promote the intelligent transformation and upgrading of industries, actively play the "smart dividend", guide domestic manufacturing enterprises to apply smart technology, promote the upgrading of domestic manufacturing industries, and thus improve the technological complexity of exports.

It should be noted that limited to the researcher's current level of knowledge, effort and access to data resources, this study needs to be further developed and refined in the following areas. One is the constraint, based on practical conditions, that prevented the researcher from conducting a field and accurate examination of individual countries. Research can only be based on the latest WIOD, UN and individual country published statistics, etc. There is no guarantee that the data is exaggerated or misrepresented. In future studies, further research is still needed to obtain more accurate data and to explore and refine more relevant indicators. Secondly, as it is not the focus of this paper, this study does not examine whether the age structure within the ageing population has an impact on the technological complexity of exporting, which can be further explored in a subsequent series of studies.

Author Contributions: Conceptualization, K.W. and L.Z.; methodology, K.W.; software, K.W.; validation, K.W. and L.Z.; formal analysis, K.W.; investigation, K.W. and L.Z.; resources, L.Z.; data curation, L.Z.; writing—original draft preparation, K.W.; writing—review and editing, K.W.; visualization, K.W.; supervision, Z.T.; project administration, L.Z.; funding acquisition, L.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by The National Social Science Fund of China, grant number 20CJY009. The APC was funded by Sichuan New Think Tank Research Project, grant number SCZKKT2021015.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used for this study were obtained from World Input-Output Database 2000–2014, Penn World Table 2000–2014, and UN demographic data.

Conflicts of Interest: The authors declare that they have no conflict of interest.

References

1. Lutz, W.; Sanderson, W.; Scherbov, S. The coming acceleration of global population ageing. *Nature* **2008**, *451*, 716–719. [CrossRef]
2. United Nations, Department of Economic, and Population Division Social Affairs. *World Population Prospects 2019: Data Booklet (St/Esa/Ser. A/424)*; United Nations: New York, NY, USA, 2019.
3. Jarzebski, M.P.; Elmqvist, T.; Gasparatos, A.; Fukushi, K.; Eckersten, S.; Haase, D.; Goodness, J.; Khoshkar, S.; Saito, O.; Takeuchi, K.; et al. Ageing and population shrinking: Implications for sustainability in the urban century. *Npj Urban Sustain.* **2021**, *1*, 17. [CrossRef]
4. Cutler, D.M.; Poterba, J.M.; Sheiner, L.M.; Summers, L.H.; Akerlof, G.A. An aging society: Opportunity or challenge? *Brook. Pap. Econ. Act.* **1990**, *1990*, 1–73. [CrossRef]
5. Dumay, J.; Rooney, J. Dealing with an ageing workforce: Current and future implications. *J. Hum. Resour. Costing Account.* **2011**, *15*, 174–195. [CrossRef]
6. Walker, A. The economic 'burden'of ageing and the prospect of intergenerational conflict. *Ageing Soc.* **1990**, *10*, 377–396. [CrossRef]
7. Kings, J.; Turkisch, E.; Manning, N. *Public Sector Pensions and the Challenge of an Ageing Public Service*; OECD Publishing: Paris, France, 2007.
8. Lührmann, M. *Effects of Population Ageing on Aggregated UK Consumer Demand*; IFS: Linköping, Sweden; CEMMAP: London, UK, 2008.
9. Domínguez-Rué, E.; Nierling, L. *Ageing and Technology: Perspectives from the Social Sciences*; Transcript Verlag: Bielefeld, Germany, 2016.
10. Adams, B. *Green Development: Environment and Sustainability in a Developing World*; Routledge: London, UK, 2019.
11. Guan, X.; Wei, H.; Lu, S.; Su, H. Mismatch distribution of population and industry in China: Pattern, problems and driving factors. *Appl. Geogr.* **2018**, *97*, 61–74. [CrossRef]
12. Kim, S.W.; Kong, J.H.; Lee, S.W.; Lee, S. Recent Advances of Artificial Intelligence in Manufacturing Industrial Sectors: A Review. *Int. J. Precis. Eng. Manuf.* **2021**, *23*, 111–129. [CrossRef]
13. Nguyen, H.; Tran, K.; Zeng, X.; Koehl, L.; Castagliola, P.; Bruniaux, P. Industrial Internet of Things, big data, and artificial intelligence in the smart factory: A survey and perspective. In Proceedings of the ISSAT International Conference on Data Science in Business, Finance and Industry, Da Nang, Vietnam, 3–5 July 2019; pp. 72–76.

14. International Federation of Robotics. *World Robotics: Industrial Robots*; Kawasaki Heavy Industries, Ltd.: Tokyo, Japan, 2019.
15. Manyika, J.; Lund, S.; Chui, M.; Bughin, J.; Woetzel, J.; Batra, P.; Sanghvi, S. *Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation*; McKinsey Global Institute: San Francisco, CA, USA, 2017; Volume 150.
16. Hajkowicz, S.; Karimi, S.; Wark, T.; Chen, C.; Evans, M.; Rens, N.; Moffatt, C. Artificial intelligence: Solving problems, growing the economy and improving our quality of life. Commonwealth Scientific and Industrial Research Organisation (CSIRO), 2019. Strategy. Available online: https://apo.org.au/node/268341 (accessed on 1 September 2022).
17. Wang, H.; Xu, Z.; Fujita, H.; Liu, S. Towards felicitous decision making: An overview on challenges and trends of Big Data. *Inf. Sci.* **2016**, *367*, 747–765. [CrossRef]
18. Vaidya, S.; Ambad, P.; Bhosle, S. Industry 4.0–a glimpse. *Procedia Manuf.* **2018**, *20*, 233–238. [CrossRef]
19. Cheng, G.-J.; Liu, L.-T.; Qiang, X.-J.; Liu, Y. Industry 4.0 development and application of intelligent manufacturing. In Proceedings of the 2016 International Conference on Information System and Artificial Intelligence (ISAI), Hongkong, China, 24–26 June 2016; pp. 407–410.
20. Gu, L. The Impact of Intelligent Manufacturing on Export Sophistication: Evidence from Industrial Robots. *Int. J. Bus. Manag.* **2021**, *14*, 183. [CrossRef]
21. Duft, G.; Durana, P. Artificial intelligence-based decision-making algorithms, automated production systems, and big data-driven innovation in sustainable industry 4.0. *Econ. Manag. Financ. Mark.* **2020**, *15*, 9–18.
22. Mamedov, O.; Tumanyan, Y.; Ishchenko-Padukova, O.; Movchan, I. Sustainable economic development and post-economy of artificial intelligence. *Entrep. Sustain. Issues* **2018**, *6*, 1028–1040. [CrossRef]
23. Hausmann, R.; Hwang, J.; Rodrik, D. What you export matters. *J. Econ. Growth* **2007**, *12*, 1–25. [CrossRef]
24. How Michigan's Economy Benefits. International Trade and Investment. 1978. Available online: https://tradepartnership.com/wp-content/uploads/2016/02/BRT_TRADE_2015_Michigan.pdf (accessed on 1 September 2022).
25. Van Marrewijk, C. *International Trade*; Oxford University Press: Oxford, UK, 2017.
26. Coale, A.J.; Hoover, E.M. *Population Growth and Economic Development*; Princeton University Press: Princeton, NJ, USA, 2015; Volume 2319.
27. Fougère, M.; Mérette, M. *Population Ageing and the Current Account in Selected OECD Countries*; Department of Finance: Oshawa ON, Canada, 1998.
28. Chinn, M.D.; Prasad, E.S. Medium-term determinants of current accounts in industrial and developing countries: An empirical exploration. *J. Int. Econ.* **2003**, *59*, 47–76. [CrossRef]
29. Kim, S.; Lee, J.-W. Demographic Changes, Saving, and Current Account in East Asia. *Asian Econ. Pap.* **2007**, *6*, 22–53. [CrossRef]
30. Gruber, J.W.; Kamin, S.B. Explaining the global pattern of current account imbalances. *J. Int. Money Financ.* **2007**, *26*, 500–522. [CrossRef]
31. Sayan, S. Heckscher–Ohlin revisited: Implications of differential population dynamics for trade within an overlapping generations framework. *J. Econ. Dyn. Control* **2005**, *29*, 1471–1493. [CrossRef]
32. Naito, T.; Zhao, L. Aging, transitional dynamics, and gains from trade. *J. Econ. Dyn. Control* **2009**, *33*, 1531–1542. [CrossRef]
33. Yakita, A. Different demographic changes and patterns of trade in a Heckscher–Ohlin setting. *J. Popul. Econ.* **2011**, *25*, 853–870. [CrossRef]
34. Zuo, X.; Yang, X. The long-term impact on the Chinese economy of an aging population. *Soc. Sci. China* **2009**, *30*, 197–208. [CrossRef]
35. Tian, W.; Yao, Y.; Yu, M.; Zhou, Y. Demography and international trade. In *University of Wisconsin-Madison Fall 2011 Workshop Working Paper*; University of Wisconsin-Madison: Madison, WI, USA, 2011.
36. Graetz, G.; Michaels, G. *Robots at Work: The Impact on Productivity and Jobs*; Centre for Economic Performance, LSE: London, UK, 2015.
37. Wang, G.; Sun, G.; Cao, W. The Quality of Exports based on China-India and Its Comparative Research—From the perspective of trade in value added. In Proceedings of the 2017 5th International Education, Economics, Social Science, Arts, Sports and Management Engineering Conference (IEESASM 2017), Qingdao, China, 28–29 December 2017; Atlantis Press: Amsterdam, The Netherlands, 2018; pp. 196–203. [CrossRef]
38. Brockova, K.; Lipková, L.; Grešš, M.; Karpenko, L. Qualitative Changes in China′s Foreign Trade in the Era of" New Normal". *Ekon. Cas.* **2020**, *68*, 1126–1151. [CrossRef]
39. Wu, F.; Yang, H.; Gao, B.; Gu, Y. Old, not yet rich? The impact of population aging on export upgrading in developing countries. *China Econ. Rev.* **2021**, *70*, 101707. [CrossRef]
40. Chai, T.-Y. Development directions of industrial artificial intelligence. *Acta Autom. Sin.* **2020**, *46*, 2005–2012.
41. Lichtenberg, F.R. The Output Contributions Of Computer Equipment And Personnel: A Firm-Level Analysis. *Econ. Innov. New Technol.* **1995**, *3*, 201–218. [CrossRef]
42. Shao, B.; Lin, W. Measuring the value of information technology in technical efficiency with stochastic production frontiers. *Inf. Softw. Technol.* **2001**, *43*, 447–456. [CrossRef]
43. Brynjolfsson, E.; Hitt, L.M. Computing Productivity: Firm-Level Evidence. *Rev. Econ. Stat.* **2003**, *85*, 793–808. [CrossRef]
44. Jorgenson, D.W.; Ho, M.S.; Stiroh, K.J. A Retrospective Look at the U.S. Productivity Growth Resurgence. *J. Econ. Perspect.* **2008**, *22*, 3–24. [CrossRef]

45. Gholami, R.; Moshiri, S.; Lee, S.Y.T. ICT and Productivity of the Manufacturing Industries in Iran. *Electron. J. Inf. Syst. Dev. Ctries.* **2004**, *19*, 1–19. [CrossRef]
46. Hawash, R.; Lang, G. *The Impact of Information Technology on Productivity in Developing Countries*; Faculty of Management Technology Working Paper; Faculty of Management Technology: Cairo, Egypt, 2010.
47. Bassetti, T.; Galvez, Y.B.; Pavesi, F.; Del Sorbo, M. *Artificial Intelligence: Impact on Total Factor Productivity, E-Commerce & Fintech*; Publications Office of the European Union: Luxembourg, 2020.
48. Graetz, G.; Michaels, G. Robots at work. *Rev. Econ. Stat.* **2018**, *100*, 753–768. [CrossRef]
49. Acemoglu, D.; Restrepo, P. Artificial intelligence, automation, and work. In *The Economics of Artificial Intelligence: An Agenda*; University of Chicago Press: Chicaga, IL, USA, 2018; pp. 197–236.
50. Papagiannidis, S.; Marikyan, D. Smart offices: A productivity and well-being perspective. *Int. J. Inf. Manag.* **2020**, *51*, 102027. [CrossRef]
51. Wu, H.; Hao, Y.; Ren, S.; Yang, X.; Xie, G. Does internet development improve green total factor energy efficiency? Evidence from China. *Energy Policy* **2021**, *153*, 112247. [CrossRef]
52. Li, Y.; Deng, J.; Hu, Z.; Gong, B. Economic Policy Uncertainty, Industrial Intelligence, and Firms' Labour Productivity: Empirical Evidence from China. *Emerg. Mark. Financ. Trade* **2020**, 1–17. [CrossRef]
53. Jiang, J.; Su, P.; Ge, Z. The high-and new-technology enterprise identification, marketization process and the total factor productivity of enterprise. *Kybernetes* **2020**, *50*, 528–549. [CrossRef]
54. Kromann, L.; Malchow-Møller, N.; Skaksen, J.R.; Sørensen, A. Automation and productivity—A cross-country, cross-industry comparison. *Ind. Corp. Chang.* **2020**, *29*, 265–287. [CrossRef]
55. Brynjolfsson, E.; Rock, D.; Syverson, C. Artificial intelligence and the modern productivity paradox: A clash of ex-pectations and statistics. In *The Economics of Artificial Intelligence: An Agenda*; University of Chicago Press: Chicaga, IL, USA, 2018; pp. 23–57.
56. Gordon, R.J. Why Has Economic Growth Slowed When Innovation Appears to be Accelerating? National Bureau of Economic Research: Cambridge, MA, USA, 2018.
57. Pajarinen, M.; Rouvinen, P. Computerization threatens one third of Finnish employment. *ETLA Brief* **2014**, *22*, 2014.
58. Frey, C.B.; Osborne, M.A. The future of employment: How susceptible are jobs to computerisation? *Technol. Forecast. Soc. Chang.* **2017**, *114*, 254–280. [CrossRef]
59. Dauth, W.; Findeisen, S.; Südekum, J.; Woessner, N. *German Robots-the Impact of Industrial Robots on Workers*; CEPR Discussion Paper No. DP12306; Elsevier: Amsterdam, The Netherlands, 2017.
60. Smith, P.; Waldeau, N. Artificial Intelligence in Workforce. *Eur. Sch. J.* **2021**, 2.
61. Tschang, F.T.; Almirall, E. Artificial Intelligence as Augmenting Automation: Implications for Employment. *Acad. Manag. Perspect.* **2021**, *35*, 642–659. [CrossRef]
62. Mutascu, M. Artificial intelligence and unemployment: New insights. *Econ. Anal. Policy* **2021**, *69*, 653–667. [CrossRef]
63. Clauberg, R. Challenges of digitalization and artificial intelligence for modern economies, societies and management. *RUDN J. Econ.* **2020**, *28*, 556–567. [CrossRef]
64. Abeliansky, A.; Prettner, K. Automation and Demographic Change. Available online: https://ssrn.com/abstract=2959977 (accessed on 14 July 2022).
65. Acemoglu, D.; Restrepo, P. Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation. *Am. Econ. Rev.* **2017**, *107*, 174–179. [CrossRef]
66. Ruiz-Real, J.L.; Uribe-Toril, J.; Torres Arriaza, J.A.; de Pablo Valenciano, J.A. A Look at the Past, Present and Future Research Trends of Artificial Intelligence in Agriculture. *Agronomy* **2020**, *10*, 1839. [CrossRef]
67. Abuselidze, G.; Mamaladze, L. The impact of artificial intelligence on employment before and during pandemic: A comparative analysis. *J. Phys. Conf. Ser.* **2021**, *1840*, 012040. [CrossRef]
68. Nazareno, L.; Schiff, D.S. The impact of automation and artificial intelligence on worker well-being. *Technol. Soc.* **2021**, *67*, 101679. [CrossRef]
69. Schultz, T.W. The Economic Importance of Human Capital in Modernization. *Educ. Econ.* **1993**, *1*, 13–19. [CrossRef]
70. Feldstein, M.; Horioka, C. The Solow growth model. *Q. J. Econ.* **1992**, *107*, 407–437.
71. Arrow, K.J. The Economic Implications of Learning by Doing. In *Readings in the Theory of Growth*; Springer Science and Business Media LLC: Berlin, Germany, 1971; pp. 131–149.
72. Crouch, C. Redefining labour relations and capital in the digital age. *Praise Work. Digit. Age* **2018**, *187*, 210–211.
73. Backes-Gellner, U.; Schneider, M.R.; Veen, S. Effect of Workforce Age on Quantitative and Qualitative Organizational Performance: Conceptual Framework and Case Study Evidence. *Organ. Stud.* **2011**, *32*, 1103–1121. [CrossRef]
74. Disney, R.; Disney, R.F. *Can We Afford to Grow Older? A Perspective on the Economics of Aging*; MIT Press: Cambridge, MA, USA, 1996.
75. Sadahiro, A.; Shimasawa, M. The computable overlapping generations model with an endogenous growth mecha-nism. *Econ. Model.* **2003**, *20*, 1–24. [CrossRef]
76. Gehringer, A.; Prettner, K. Longevity and Technological Change. *Macroecon. Dyn.* **2019**, *23*, 1471–1503. [CrossRef]
77. Verhaeghen, P.; Salthouse, T.A. Meta-analyses of age–cognition relations in adulthood: Estimates of linear and nonlinear age effects and structural models. *Psychol. Bull.* **1997**, *122*, 231–249. [CrossRef] [PubMed]
78. Chui, M.; Manyika, J.; Miremadi, M. Four fundamentals of workplace automation. *McKinsey Q.* **2015**, *29*, 1–9.

79. Autor, D.; Salomons, A. *Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share*; National Bureau of Economic Research: Cambridge, MA, USA, 2018. [CrossRef]
80. World Bank. World Development Indicators. 2016. Available online: https://databank.worldbank.org/data/reports.aspx (accessed on 1 July 2022).
81. Chen, Y.; Lin, C.; Chen, X. Artificial intelligence, ageing and economic growth. *Econ. Stud.* **2019**, *7*, 47–63.
82. Aghion, P.; Jones, B.F.; Jones, C.I. Artificial intelligence and economic growth. In *The Economics of Artificial Intelli-Gence: An Agenda*; University of Chicago: Press: Chicaga, IL, USA, 2018; pp. 237–282.
83. Paul, D.; Sanap, G.; Shenoy, S.; Kalyane, D.; Kalia, K.; Tekade, R.K. Artificial intelligence in drug discovery and de-velopment. *Drug Discov. Today* **2021**, *26*, 80. [CrossRef] [PubMed]
84. WIOD. World Input–Output Database. 2016. Available online: https://www.rug.nl/ggdc/valuechain/wiod/wiod-2016-release (accessed on 1 September 2022).
85. Wang, Z.; Wei, S.-J.; Yu, X.; Zhu, K. Tracing Value Added in the Presence of Foreign Direct Investment. *Natl. Bur. Econ. Res.* **2021**, w29335. [CrossRef]
86. Acemoglu, D.; Restrepo, P. Robots and Jobs: Evidence from US Labor Markets. *J. Politi- Econ.* **2020**, *128*, 2188–2244. [CrossRef]
87. World Bank. *World Bank Atlas 2002*; The World Bank: Washington, DC, USA, 2002.
88. Brook, R.J.; Arnold, G.C. *Applied Regression Analysis and Experimental Design*; CRC Press: Boca Raton, FL, USA, 2018.
89. Zhang, L.P.; Jiang, W. Does the relationship between government and enterprises affect the capacity utilization of Chinese manufacturing firms? *Ind. Econ. Res.* **2015**, *6*, 82–90.
90. Acemoglu, D.; Restrepo, P. Demographics and automation. *Rev. Econ. Stud.* **2022**, *89*, 1–44. [CrossRef]