sustainability

Article

Has Artificial Intelligence Promoted Manufacturing Servitization: Evidence from Chinese Enterprises

Daxing Chen, Helian Xu and Guangya Zhou *

School of Economics and Trade, Hunan University, Changsha 410079, China; chendx1993@hnu.edu.cn (D.C.); xuhelian@163.com (H.X.)
* Correspondence: zhougyemail@163.com; Tel.: +86-18811779212

Abstract: Artificial intelligence, as a novel form of infrastructure with both generality and knowledge spillover characteristics, plays a crucial role in facilitating the profound integration of the manufacturing and service industries, and achieving economic transformation. This paper empirically investigates the impacts of artificial intelligence on the process of manufacturing servitization, utilizing merged data from the OECD-ICIOT (Organization for Economic Co-operation and Development, Intercountry Input-Output Tables) industry data, the Chinese industrial enterprise database, and the customs trade database. The empirical findings of this research demonstrate that artificial intelligence has significant and positive effects on manufacturing servitization. These positive effects primarily occur through two channels: enhancing total factor productivity and optimizing the labor skill structure. Furthermore, this study examines the variations in the impact of artificial intelligence on the transformation of embedded services and blended services. The analysis reveals that artificial intelligence significantly promotes the transformation of embedded services, while its impact on the transformation of blended services is comparatively less pronounced.

Keywords: artificial intelligence; manufacturing servitization; labor skill structure; service transformation

check for updates

Citation: Chen, D.; Xu, H.; Zhou, G. Has Artificial Intelligence Promoted Manufacturing Servitization: Evidence from Chinese Enterprises. *Sustainability* **2024**, *16*, 2526. https://doi.org/10.3390/su16062526

Academic Editor: Malgorzata Jasiulewicz-Kaczmarek

Received: 8 January 2024
Revised: 13 March 2024
Accepted: 16 March 2024
Published: 19 March 2024

1. Introduction

Manufacturing servitization is a crucial strategic initiative aimed at aligning with the ongoing international industrial transformation, propelling China's industries towards the mid-to-high tiers of the global value chain, and facilitating the transition to high-quality economic development. The emergence of the intelligent era, epitomized by artificial intelligence, is ushering in a new phase of the industrial revolution, serving as a catalyst for the transformation towards manufacturing servitization. The 19th National Congress of the Communist Party of China emphasized the imperative to "accelerate the development of advanced manufacturing, promote the deep integration of the internet, big data, artificial intelligence, and the real economy". Moreover, "Made in China 2025" refines the overarching direction by outlining the nation's commitment to constructing a manufacturing powerhouse characterized by high-end sophistication, intelligence, environmental sustainability, and a service-oriented approach.

Furthermore, an undeniable fact is that in recent years, China's economic development has shown a significant weakening of the comparative advantage derived from traditional low-cost resources and factor inputs. The development model relying on extensive factor inputs and export-driven growth is considered unsustainable. The impetus for China's high-quality economic development now lies in the industrial revolution centered on digitization, networking, and intelligence. Simultaneously, in the post-pandemic era, developed countries such as the United States, Europe, and Japan have successively introduced "reindustrialization" strategies anchored in smart manufacturing to reshape their international leading position in high-end manufacturing through digitization and intelligence. Given this context, conducting a comprehensive exploration of the impacts and mechanisms of artificial intelligence on the level of manufacturing servitization is of great significance for China's journey towards becoming a manufacturing powerhouse and achieving the transformation and upgrading of its manufacturing industry.

In the contemporary business landscape, the widespread adoption of artificial intelligence (AI), big data, and the Internet of Things (IoT) has become a defining characteristic, leading to significant technological advancements, open innovation, and collaboration [1]. This trend is particularly prominent in the manufacturing industry, often referred to as Industry 4.0 or the Fourth Industrial Revolution [2–4]. Consequently, research focusing on the application of AI in manufacturing enterprises offers valuable insights for our study [5]. For example, in a study conducted by Christian Stadlmann, the utilization of AI in web sales for companies operating in the advanced manufacturing sector was analyzed [6]. Several scholars have also examined the relationship between AI and servitization, exploring it from the perspective of dynamic capabilities [7] and within the context of Servitization 5.0 [8]. These scholars have conducted an analysis of the inverse U-shaped impact of AI-driven manufacturing intelligence on innovation performance [9], as well as an investigation into how various AI-based solutions support firms in co-creating value within the B2B (Business to Business) industrial market [10].

Furthermore, other researchers have analyzed how existing enterprises in the manufacturing industry can use artificial intelligence to achieve business model innovation in the industrial ecosystem [11,12]. These findings provide empirical insights into the intermediate development steps toward AI-driven business model innovation by leading manufacturers engaged in digital servitization. They also provide an in-depth characterization of AI capabilities and key principles for business model innovation as a means to assimilate AI into business practice [13]. Moreover, studies have also explored how the application of AI in manufacturing enterprises enhances resource efficiency, underscoring the importance of integrating sustainability with AI solutions [14].

In addition to these studies, two other literature sources also contribute significant implications to this research. The first category of literature focuses on the various roles of AI in the economic and social domains. As a new generation of information technology, the collaborative nature of AI features enhances input-output efficiency or total factor productivity, ultimately resulting in GDP growth [15]. Some scholars' research indicates that AI can effectively address the challenges of aging populations [16], and AI and natural resource management contribute to economic growth [17]. The conclusions of another set of literature confirm the promoting effect of AI on productivity [18], primarily through reducing labor demand [19,20] and substituting cheaper capital for labor [21]. Some scholars also point out that AI is essentially a factor-expanding technology, which is beneficial for improving production efficiency [22].

Research on the impact of AI on employment has not yet reached a consensus. Some scholars' research shows that the productivity improvement effect of AI leads to expanded production by firms, thereby increasing employment opportunities [23]. Furthermore, while AI displaces employment in certain industries, it also creates new types of jobs through "creation effects," thereby causing changes in the overall employment structure [24]. The negative impact of AI on employment mainly manifests in the polarization of employment resulting from AI shocks [25,26]. The research of the vast majority of scholars shows that AI significantly reduces the share of low-skilled workers in employment [27], and this employment structure leads to an expanding income gap between low-skilled and high-skilled workers [28].

Another category of literature analyzes the driving mechanisms and economic effects of manufacturing servitization. Manufacturing servitization creates new value by integrating products and services [29]. Thus, manufacturing servitization significantly improves firms' innovation performance [30] and is an effective approach for reshaping their competitive advantages and achieving sustainable development [31]. Manufacturing servitization facilitates the strengthening of cooperation in the global value chain division of labor and the embeddedness of various clusters within the value chain network [32], thereby significantly enhancing firms' position in the global value chain [33–35]. From this perspective, the higher the division of labor position of manufacturing in the global value chain, the greater the productivity effect of servitization [36]. Regarding the export effects of manufacturing servitization, the research of the vast majority of scholars indicates that the transformation of manufacturing inputs into services accelerates the process of firms' export upgrading from "quantity-oriented" to "quality-oriented" [37], but this effect exhibits industry heterogeneity [38]. Furthermore, some literature examines the impact of manufacturing servitization on firm performance, yielding three different viewpoints: promotion [39,40], inhibition [41], and nonlinear relationships [42,43].

On the other hand, independent innovation is an important driving force for the servitization of the manufacturing industry [44]. This is because the improvement in product innovation capabilities enables manufacturers to provide customized services to customers through product design enhancement and the manufacturing of new products, thereby promoting the transformation towards a service-oriented development [29]. Some literature also examines the positive impact of internet technologies [45] and digital finance [46] on the servitization of the manufacturing industry. Scholars have also analyzed the impact of research and development personnel ratio, input intensity, and the proportion of clean energy from an ecological perspective on the servitization of the manufacturing industry [47]. Furthermore, some scholars have studied the role of manufacturing servitization in reducing firms' emission intensity [48]. From the perspective of international industrial evolution trends and development patterns, the transformation and upgrading of the manufacturing industry rely on the support of productive service industries [49].

Overall, existing literature on the economic effects of manufacturing servitization is relatively abundant, but there is relatively little research on how to achieve manufacturing servitization. Moreover, existing literature only discusses this issue from the perspective of the development of productive service industries, with few studies incorporating artificial intelligence and manufacturing servitization into a unified analytical framework to directly examine the impact of AI development on manufacturing servitization. Therefore, this article seeks to empirically study the impact of artificial intelligence on the manufacturing industry, based on matched data from the OECD-ICIOT (Organization for Economic Co-operation and Development, Intercountry Input-Output Tables) industry data, the China Industrial Enterprise Database, and the Customs Trade Database. The aim is to provide valuable insights on how to leverage the positive role of artificial intelligence in the manufacturing sector. The research findings indicate that artificial intelligence significantly and robustly enhances the level of servitization in manufacturing enterprises. This effect is primarily achieved through two channels: improving enterprise total factor productivity and optimizing the labor skill structure. Furthermore, when distinguishing between different ways of transforming manufacturing services, this study reveals that artificial intelligence plays a significant facilitating role in the embedded service transformation, while its impact on the blended service transformation is not evident.

This paper contributes to three main aspects in comparison to previous research. Firstly, it accurately measures the level of manufacturing servitization at the enterprise level by distinguishing between domestic and foreign factor inputs. This enables the provision of micro-level evidence on how artificial intelligence influences manufacturing servitization. Secondly, it extends the analysis framework of domestic value-added in exports proposed by Kee and Tang [50] to the field of manufacturing servitization. The paper constructs a theoretical framework that incorporates the constraints of artificial intelligence inputs and labor skill inputs. Using this framework, it explores the theoretical mechanisms through which artificial intelligence affects manufacturing servitization within a general equilibrium framework, considering the impact on enterprise total factor productivity and the optimization of labor skill structure. Thirdly, the paper further distinguishes manufacturing servitization into embedded services and hybrid services, providing clarification on the differentiated effects of different types of service transformations. Fourthly, it enriches the positive role of artificial intelligence in the manufacturing sector, providing a good inspiration for China to better integrate artificial intelligence with the real economy, build manufacturing power, and promote the development of the intelligent era.

The subsequent structure of this paper is as follows: Section 2 provides a theoretical analysis and presents the hypotheses of this study. The complete model derivation process can be found in Appendix A. Section 3 describes the econometric model, data sources, and relevant indicator explanations. Section 4 presents the empirical results analysis and discussion. Section 5 further examines the differential effects of artificial intelligence on the transformation of embedded services and hybrid services. Finally, the main research conclusions and policy implications are presented.

2. Theoretical Mechanism and Hypothesis

This paper expands upon the framework introduced by Kee and Tang [50] that focuses on firms exporting domestic value-added, and extends it to the domain of manufacturing servitization. By integrating this framework with the artificial intelligence technology model presented by Acemoglu and Restrepo [19], the paper investigates, within a unified analytical framework, the impact of artificial intelligence on the extent of manufacturing servitization. The complete and detailed mathematical derivation process can be found in Appendix A.

Based on the research conducted by Acemoglu and Restrepo [19], it is clear that the adoption of artificial intelligence significantly enhances the total factor productivity of enterprises. This conclusion has been supported by other scholars, including Graetz and Michaels [18] and Aghion et al. [51]. Based on this, the following hypothesis can be derived:

Hypothesis 1: The adoption of artificial intelligence improves the overall factor productivity of enterprises, leading to an increase in the level of servitization within the manufacturing industry.

To gain a deeper understanding of the labor structure, we explore the implications of artificial intelligence investment on the framework of the labor market. We assume that a firm's labor input (L) consists of both low-skilled labor (L^u) and high-skilled labor (L^s), with the proportion of low-skilled labor represented by σ. Building upon the research conducted by Krusell et al. [52] and Lankisch et al. [53], we propose a significant substitutive relationship between a firm's AI input and low-skilled labor (L^u), while high-skilled labor (L^s) remains non-substitutable. From this, the second theoretical mechanism through which artificial intelligence influences the level of servitization in manufacturing enterprises can be derived.

Hypothesis 2: Artificial intelligence enhances manufacturing servitization by substituting low-skilled labor.

3. Research Design

3.1. Model Setup

Drawing upon the theoretical analysis process and hypothesis 1, this paper establishes a baseline model to investigate the influence of artificial intelligence on manufacturing servitization:

$$Servitization_{fit} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 Control_{fit} + \delta_f + \eta_t + \varepsilon_{fit} \tag{1}$$

In this context, the subscripts *f*, *i*, and *t* denote the firm, industry, and year, respectively. The variable "Servitization" represents the level of manufacturing servitization within a firm, while "*AI*" denotes the level of artificial intelligence in the industry. Additionally, "*Control*" stands for the control variables. The terms δ_f and η_t represent firm-specific fixed effects and year-fixed effects, respectively. Moreover, the residual term ε_{fit} follows a normal distribution.

3.2. Explanation of Indicators

The level of manufacturing servitization serves as the dependent variable in this paper. To calculate the industry-level domestic and foreign service input structure, we utilize input-output data published by the OECD. Following the methodology employed by

Deng et al. [48], the manufacturing servitization index at the enterprise level is constructed by employing the enterprise's domestic and foreign value-added rates as weighting factors. The larger the index, the higher the level of manufacturing servitization.

The primary explanatory variable in this study is the extent of AI implementation. The advancement of AI within a specific industry is typically manifested by the continuous growth of AI enterprises catering to that industry [54,55]. To identify artificial intelligence enterprises in the Chinese industrial database, we employ techniques such as company and product name recognition. Subsequently, we calculate the proportion of AI enterprises within two-digit industries relative to the total number of enterprises, which serves as a metric for assessing the level of artificial intelligence development in each industry. Additionally, to ensure robustness, we incorporate industry robot usage data provided by the International Federation of Robotics (IFR) as an alternative indicator for AI, considering that the existing literature commonly employs the quantity of industry robot usage as a measure of AI [18].

Furthermore, this study incorporates several additional control variables (referred to as "Control") that influence the servitization of manufacturing enterprises. These variables include the following:

1. Firm age (lnage) is measured as the natural logarithm of the duration in years, calculated by subtracting the year of establishment from the current year and adding one.
2. Firm size (lnsize) is represented by the natural logarithm of the number of employees.
3. Total factor productivity (lntfp) is calculated using the extended Olley and Pakes (1996) method.
4. Ownership structure (Ownership) is classified into various categories based on the ratio of actual registered capital. These categories include state-owned enterprises (State), collective enterprises (Collective), legal entities (Legal), private enterprises (Private), Hong Kong, Macao, and Taiwan-funded enterprises (HMT), and foreign-funded enterprises (Foreign). State-owned enterprises are used as the baseline in specific regressions, with other types of enterprises included in the econometric model.
5. Industry competition level (HHI) is determined using the Herfindahl–Hirschman Index (HHI) for two-digit industries. The formula used for computation is as follows: $hhi = \sum_{f=1}^{n} (sales_{fi} / \sum_{f=1}^{n} sales_{fi})^2$, where sales denotes the sales revenue of enterprise f in industry i.

3.3. Source of Data

The study's sample period spans from 2005 to 2015, and the relevant data primarily originate from the following databases. Firstly, the ICIOT published by the OECD in 2018 provide input-output data for 66 countries (regions) and 36 standard industry sectors. This database enables the estimation of domestic and foreign value added at the industry level. Secondly, the World Input-Output Database (WIOD) is utilized, connected to the Chinese Industry Classification (CIC) for input-output data. The WIOD facilitates the calculation of domestic value added absorbed by China and domestically added value with pure double-counting at the industry level. Thirdly, matching data from the industrial enterprise database and the customs database are utilized to obtain relevant indicators, including export value, intermediate inputs, output, as well as the number of employees, establishment year, and other accounting information of industrial enterprises in measuring the servitization of the manufacturing industry.

To match the aforementioned data, the study followed these steps. Firstly, two methods were employed to match the Chinese industrial enterprise database and the customs trade database. These methods involved using the company name, as well as the last seven digits of the postal code and phone number. Secondly, a comparison was made between the broad product types in the WIOD and the OECD industry classification, and the two-digit industry codes in the CIC. Subsequently, the WIOD and OECD data were matched with the Chinese industrial enterprise database based on the two-digit CIC industry codes.

Before conducting the econometric regression analysis, the following procedures were performed on the matched data, following Brandt et al.'s approach [56]. Firstly, observations with missing values for key variables, including industrial output, total assets, net value of fixed assets, and the number of employees, were excluded. Secondly, certain outlier observations were eliminated, including cases where total assets were smaller than current assets, total assets were smaller than the net value of fixed assets, accumulated depreciation was smaller than current depreciation, and observations with fewer than eight employees. Thirdly, observations from companies with only one year of data were removed. Fourthly, inspired by the method used by Crinò and Ogliari [57], all continuous variables were subjected to two-sided truncation at the 1% level. After applying the aforementioned data screening and processing steps, a final sample of 314,991 observations from 90,478 firms between 2005 and 2015 was obtained for analysis. Descriptive statistics of the relevant data are presented in Table 1.

Table 1. Descriptive Statistics of Variables.

Variables	Definition	Sample Size	Mean	S.D.	Min	Max
Servitization	Level of Manufacturing Servitization	314,991	0.2358	0.0674	0.1141	0.4371
AI	Artificial Intelligence	314,991	0.0023	0.0051	0	0.0442
lnage	Firm Age	314,991	2.0562	0.6717	0	4.6052
lnsize	Firm Size	314,991	5.1919	1.1505	2.0794	12.2880
lntfp	Total Factor Productivity of Enterprises	314,991	1.1803	1.5598	−3.3574	6.7499
State	State-owned Enterprises	314,991	0.1416	0.3486	0	1
Collective	Collective Enterprises	314,991	0.0458	0.2090	0	1
Legal	Legal Person Enterprises	314,991	0.2074	0.4054	0	1
Private	Private Enterprises	314,991	0.2298	0.4207	0	1
HMT	Enterprises from Hong Kong, Macao, and Taiwan	314,991	0.1902	0.3924	0	1
Foreign	Foreign-funded Enterprises	314,991	0.1853	0.3885	0	1
HHI	Degree of Industry Competition	314,991	0.0048	0.0144	0.0001	0.2876

4. Discussion

4.1. Baseline Regression Results

The baseline regression results of this study are presented in Table 2. Columns (1)–(2) include only time-fixed effects, and the estimated coefficient of the key explanatory variable, AI, shows a significant positive correlation with the level of manufacturing servitization. Columns (3)–(4) further incorporate firm-time fixed effects into the econometric model. The regression results confirm that the estimated coefficient of the core explanatory variable, AI, remains significantly positive at the 5% level, indicating that the development of AI technology indeed enhances the servitization level of the manufacturing industry. Based on the estimation results from Column (4), after controlling for other factors influencing the level of manufacturing servitization, a 1-unit increase in the AI level leads to a 0.5870-unit increase in the servitization level of firms in the respective industry, which holds significant economic significance.

The estimation results of the control variables in Table 2 indicate that the estimated coefficients for firm age (lnage) are consistently and significantly negative, suggesting that the upgrading of manufacturing servitization is more likely to occur in relatively "younger" firms. One possible explanation is that longer-standing firms often face issues such as outdated equipment, technological obsolescence, and lagging market responsiveness [58,59], which hinder their transformation towards servitization. The estimated coefficients for firm size (lnsize) and industry competitiveness (HHI) are not statistically significant, indicating that the level of manufacturing servitization is not significantly related to the scale of employment or the level of industry competition. The estimated coefficient for total factor productivity (lntfp) is significantly positive at the 1% level, suggesting that an improvement in total factor productivity effectively drives the transformation of firms towards manufacturing servitization. This is mainly because an increase in total factor productivity accelerates technological reserves within firms, especially with the application of internet and industrial cloud technologies, providing new development opportunities and driving the transformation from traditional product-centric production models to service-oriented approaches [60,61].

Table 2. Benchmark Regression Results.

Variables	**Dependent Variable: Servitization**			
	(1)	**(2)**	**(3)**	**(4)**
AI	1.6879 ** (0.7475)	1.5190 ** (0.6682)	0.5928 ** (0.2313)	0.5870 ** (0.2327)
lnage		−0.0006 (0.0013)		−0.0023 *** (0.0007)
lnsize		−0.0009 (0.0012)		−0.0003 (0.0004)
lntfp		0.0013 * (0.0008)		0.0004 *** (0.0001)
Collective		0.0037 *** (0.0007)		0.0023 *** (0.0006)
Legal		0.0069 *** (0.0024)		0.0033 ** (0.0015)
Private		−0.0042 *** (0.0012)		−0.0025 *** (0.0005)
HMT		0.0181 *** (0.0025)		0.0029 *** (0.0006)
Foreign		0.0231 *** (0.0015)		0.0035 *** (0.0006)
HHI		0.0434 (0.0278)		0.0095 (0.0066)
Constant	0.2339 *** (0.0056)	0.2244 *** (0.0096)	0.2341 *** (0.0006)	0.2394 *** (0.0030)
Firm Fixed Effects	No	No	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	359,168	359,168	314,991	314,991
R-squared	0.0315	0.0545	0.8104	0.8111

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered at the industry level are reported in parentheses.

Regarding the regression results for ownership structure variables, the estimation results in Column (4) show that foreign-owned enterprises have the highest level of manufacturing servitization, followed by legal entities, while private enterprises have the lowest level. Specifically, the servitization level of foreign-owned enterprises (Foreign), legal entities (Legal), enterprises from Hong Kong, Macau, and Taiwan (HMT), and collective enterprises (Collective) is respectively 0.0035, 0.0033, 0.0029, and 0.0023 higher than that of state-owned enterprises (State), while private enterprises (Private) have a servitization level 0.0025 lower than that of state-owned enterprises. This is mainly due to the fact that the level of manufacturing servitization is often constrained by financial factors [46,62]. Private enterprises face difficulties in financing and higher costs when extending the industrial value chain towards research and development and marketing [63,64]. In contrast, bank credit is more inclined to flow to foreign-owned enterprises, which have a higher resource allocation efficiency [65]. Sufficient financial support facilitates the transformation of enterprises towards servitization.

4.2. Robustness Test

To enhance the robustness and reliability of the test results, this section will conduct robustness tests related to indicator selection, econometric regression methods, mitigating other policy impacts, addressing sample selection bias, and addressing the endogeneity issue in the model.

(1) Alternative Measurement of the Core Variable: The studies by Graetz and Michaels (2018) serve as a reference, and industry data on robot usage provided by the IFR is utilized as an alternative indicator for artificial intelligence. The estimation results in column (1) of Table 3 indicate that the artificial intelligence variable remains significant at the 1% level, further confirming the robustness and reliability of the key conclusion that "artificial intelligence contributes to increasing the level of manufacturing servitization". Additionally, this study also considers the characteristics of the binary export structure in general trade and processing trade. The level of manufacturing servitization is recalculated and included as the dependent variable in the econometric regression model based on the 2016 version of the input-output data published by OECD-ICIOT. The estimation results in column (2) reveal that the estimated coefficient for AI is 0.6051, passing the 5% significance level test and providing further confirmation of the robustness of the relevant conclusions.

(2) Changing the Econometric Regression Method: Considering that the dependent variable "Servitization" is a continuous variable ranging from 0 to 1, a panel Tobit model is employed for regression. The estimation results are presented in column (3) of Table 3. After changing the estimation method, the estimated coefficient of the key explanatory variable AI remains significant, and the basic regression conclusion holds.

(3) Controlling for Other Policy Effects: Firstly, the global economic landscape was profoundly impacted by the outbreak of the financial crisis, resulting in substantial changes in corporate production and organizational methods that influenced manufacturing servitization. To address this, the paper excludes samples from the period of 2007–2008 to mitigate the influence of the financial crisis. The estimation results in column (4) of Table 3 demonstrate that, even after excluding the impact of the financial crisis, the estimated results for the AI variable remain significantly positive. Moreover, following its accession to the WTO (World Trade Organization), China experienced a substantial increase in trade liberalization, actively integrating into the global industrial division of labor to reshape trade practices and expedite manufacturing servitization. Citing the findings of Liu et al. [66], the paper incorporates time dummy variables for WTO entry and cross terms of final goods tariffs and intermediate goods tariffs into the econometric model to account for the effects of WTO accession. The estimation results in column (5) of Table 3 reveal that, after accounting for the impact of trade liberalization, the estimated coefficient of the key explanatory variable AI is 0.5244, significant at the 5% level. Finally, in 2015, the General Office of the Ministry of Industry and Information Technology issued the "Notice on Carrying Out the Recommended Demonstration Projects for Intelligent Manufacturing Pilot Projects in 2015", significantly fostering the advancement of manufacturing servitization for enterprises. Therefore, to account for the impact of this policy, the paper incorporates a virtual variable for intelligent manufacturing pilot demonstration projects and a time dummy variable into the econometric model. Simultaneously, samples from 2015 are excluded to mitigate the influence of the intelligent manufacturing pilot demonstration projects. The estimation results in columns (6)–(7) of Table 3 demonstrate that, despite controlling for the impact of intelligent manufacturing pilot projects, AI continues to significantly promote the level of manufacturing servitization through a persistently positive estimated coefficient.

(4) Sample selection bias issue. There are two types of bias encountered in this study. The first type arises from the Chinese industrial enterprise database's limited inclusion of state-owned enterprises and small and medium-sized non-enterprises above a certain scale. Prior to 2011, the statistical criteria relied on a minimum main business income

of 5 million yuan. Subsequently, the criteria increased to a minimum main business income of 20 million yuan or higher. Consequently, this discrepancy causes data gaps in the sample, inevitably introducing selection bias. Consequently, this study excludes state-owned enterprise samples with main business income below 5 million yuan prior to 2011 and below 20 million yuan thereafter. The estimation results in column (8) of Table 3 reveal that, even after excluding the statistical data defects, the estimated coefficient of the artificial intelligence variable remains significantly positive. The second type of sample problem revolves around investigating the impact of artificial intelligence on the service transformation of manufacturing enterprises, specifically by excluding non-trading enterprise samples. This approach may introduce a non-random sample issue stemming from sample self-selection. To mitigate this concern, the Heckman two-step method is employed. The estimation results in column (9) indicate that the inverse Mills ratio (IMR) does not surpass the 10% significance level test, suggesting the absence of a significant sample selection bias issue in the empirical regression analysis undertaken in this study.

(5) Endogeneity Issue. Potential endogeneity in this study arises due to a reverse causal relationship between variables. Specifically, an improvement in the level of manufacturing servitization in enterprises may lead to an increase in the level of artificial intelligence. To ensure reliable regression results concerning the impact of artificial intelligence on manufacturing servitization, this study employs the annual aggregate of articles published on artificial intelligence in the United States and the United Kingdom from 2005 to 2015 as the instrumental variable for AI. Subsequently, the employment ratio in each two-digit industry in China for each year is employed as a weighting factor to break down the instrumental variable at the industry level.

Table 3. Robustness Test Results.

Variables	Dependent Variable: Servitization										
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
AI	1.1953 *** (0.1806)	0.6051 ** (0.2736)	1.2507 *** (0.0307)	0.7353 ** (0.3120)	0.5244 ** (0.2054)	0.5870 ** (0.2327)	0.5660 ** (0.2196)	0.5864 ** (0.2332)	0.6250 ** (0.2412)		
IV										6.1578 *** (0.0929)	
AI_IV											3.6513 *** (0.0280)
IMR									0.0099 (0.0116)		
Constant	0.2394 *** (0.0013)	0.2903 *** (0.0036)	0.2374 *** (0.0007)	0.2323 *** (0.0038)	0.2394 *** (0.0029)	0.2394 *** (0.0030)	0.2394 *** (0.0029)	0.2394 *** (0.0030)	0.2262 *** (0.0163)	——	——
Enterprise Fixed Effects	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic	——	——	——	——	——	——	——	——	——	128.38 ***	
Cragg-Donald Wald F statistic	——	——	——	——	——	——	——	——	——	170.43 ***	
Observations	314,991	303,318	359,166	289,456	314,991	312,353	314,991	314,903	314,991	359,169	314,991
R-squared	0.8234	0.8278	——	0.8241	0.8111	0.8112	0.8111	0.8111	0.8111	0.782	0.816

Note: In column (1), the artificial intelligence variable is measured using industry robot usage data provided by IFR. In column (2), the dependent variable is based on input-output data published by OECD-ICIOT in the 2016 version, distinguishing between general trade and processing trade structures, and recalculating the level of manufacturing servitization. Column (3) reports the regression results of the panel Tobit model. Column (4) reports the empirical results after excluding the impact of the financial crisis. Column (5) reports the empirical results controlling for the impact of trade liberalization. Columns (6)–(7) report the empirical results controlling for the impact of the intelligent manufacturing pilot policy. Column (8) reports the empirical results after excluding the sample of state-owned enterprises with main business income below 5 million yuan before 2011 and below 20 million yuan after 2011. Column (9) reports the results considering sample selection bias and estimated using Heckman's two-step method. Columns (10)–(11) report the estimation results of two-stage least squares, *** and ** indicate statistical significance at the 1% and 5% levels, respectively, with robust standard errors clustered at the industry level in parentheses.

There are two justifications for this selection. First, as the level of artificial intelligence development rises, researchers and institutions in a country become more actively engaged in research. Furthermore, the progress in artificial intelligence technology equips researchers with stronger experiential foundations. Thus, employing research output as an instrumental variable holds some validity and is not directly linked to the level of manufacturing servitization. Second, the United States and the United Kingdom, being leading countries in artificial intelligence, have established a mature technological culture that gradually influences nations globally.

Based on a research report by the Information Technology and Innovation Foundation (ITIF), China is progressively reducing the gap in several crucial areas despite the United States' ongoing dominance in artificial intelligence capabilities. Notably, the number of research papers in the field of artificial intelligence in China exceeds that of the United States. The United Kingdom, recognized as the birthplace of artificial intelligence, stands as a frontrunner in European artificial intelligence. Moreover, its capital, London, is widely acknowledged as a global hub for artificial intelligence development, occupying a prominent position in diverse aspects such as artificial intelligence research and investment.

Consequently, the influence of research outcomes from the United States and the United Kingdom on Chinese manufacturing enterprises primarily showcases the progressive nature of artificial intelligence development, satisfies the relevance criteria of instrumental variables, and remains independent of other local factors that affect the implementation of artificial intelligence in China. Utilizing these outcomes as instrumental variables for the industry-level integration of artificial intelligence in China aids in mitigating the endogeneity problem in the model.

This study acquired data on paper output (in tens of thousands) in the field of artificial intelligence for the United States and the United Kingdom from 2005 to 2015 by performing a keyword search for artificial intelligence in article titles on Web of Science. Estimation was conducted using the two-stage least squares (2SLS) method as the instrumental variable. The estimation results of the two-stage least squares method, presented in columns (10) to (11) of Table 3, indicate a consistently positive and statistically significant estimated coefficient of AI_IV. This finding suggests a clear contribution of artificial intelligence technology to the enhancement of manufacturing servitization. Furthermore, the LM test for the instrumental variable (IV) successfully rejects the null hypothesis of "insufficient instrumental variable identification" at the 1% significance level. Moreover, the Wald F-test statistic, passing the 1% significance level test, rejects the null hypothesis of a "weak instrumental variable". This outcome provides additional confirmation of the instrumental variable's validity.

4.3. Theoretical Mechanism Testing

Building upon the analysis of theoretical mechanisms, we additionally identified Total Factor Productivity (TFP) and the proportion of low-skilled labor employment as intermediary variables. To investigate the mechanism by which artificial intelligence impacts manufacturing servitization, we utilized a mediation effect model. The following econometric model is employed:

$$lntfp_{fit} = \pi_0 + \pi_1 AI_{it} + \pi_2 Control_{fit} + \delta_f + \eta_t + \varepsilon_{fit} \tag{2}$$

$$Labor_{fit} = \gamma_0 + \gamma_1 AI_{it} + \gamma_1 Control_{fit} + \delta_f + \eta_t + \varepsilon_{fit} \tag{3}$$

$$\begin{aligned} Servitization_{fit} &= \theta_0 + \theta_1 AI_{it} + \theta_2 lntfp_{fit} + \theta_3 Labor_{fit} + \theta_4 Control_{fit} + \delta_f \\ &+ \eta_t + \varepsilon_{fit} \end{aligned} \tag{4}$$

In this context, the variable 'Labor' represents the proportion of low-skilled labor employment. This study utilizes the employment structure data from the enterprise-level by matching the data from the 2008 China Economic Census Database with the industrial enterprises-customs integration dataset. Furthermore, the variable 'Labor' is measured by the proportion of employees with college degrees or below to the total number of individuals employed by the enterprise at the end of the year. Other variables in the model and parameter explanations are the same as in the previous context.

The estimation results in the middle column (1) of Table 4 demonstrate that the application of artificial intelligence significantly enhances a company's TFP. Furthermore, the results in column (2) indicate a significant positive correlation between company TFP and the level of manufacturing servitization, confirming theoretical hypothesis 1 that artificial intelligence will improve manufacturing servitization by promoting company TFP. Similarly, the estimation results in columns (3)–(4) of Table 4 show that the regression coefficient of artificial intelligence on the proportion of low-skilled labor employment is −7.2206. This implies that an increase of 1 unit in artificial intelligence level leads to a decrease of 7.2206 units in the proportion of low-skilled labor employment. Simultaneously, for every 1-unit increase in the proportion of low-skilled labor employment, the level of manufacturing servitization decreases by 0.0191. This result verifies theoretical hypothesis 2 that artificial intelligence enhances manufacturing servitization by reducing the input of low-skilled labor. According to the Sobel test, the Z-values for both intermediary variables are greater than 0.97 at the 5% significance level, indicating a significant intermediary effect. In other words, artificial intelligence can influence the manufacturing servitization level of a company through the two channels mentioned above. Examining the proportion of different intermediary effects, it is evident that the impact of artificial intelligence on TFP improvement is much smaller than the effect of optimizing the labor structure.

Table 4. Results of the Mechanism Test.

Part A: Results of the Mediation Effect Test					
Variables	lntfp	Servitization	Labor	Servitization	Servitization
	(1)	(2)	(3)	(4)	(5)
AI	2.1393 *	0.5870 **	−7.2206 ***	0.4399 *	0.4400 *
	(1.2493)	(0.2327)	(1.4921)	(0.2280)	(0.2277)
lntfp		0.0004 ***			0.0004 ***
		(0.0001)			(0.0001)
Labor				−0.0191*	−0.0191 *
				(0.0107)	(0.0107)
Control Variables	Yes	Yes	Yes	Yes	Yes
Constant	−0.9379 ***	0.2394 ***	0.8418 ***	0.2554 ***	0.2555 ***
	(0.1331)	(0.0030)	(0.0063)	(0.0092)	(0.0092)
Enterprise Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	443,658	314,991	443,284	314,618	314,618
R-squared	0.5829	0.8111	0.9135	0.8111	0.8112

Part B: Mediation Effect Test							
	c	a	σ_a	b	σ_b	z	Intermediary effect weight
lntfp	0.4400	2.1393	1.2493	0.0004	0.0001	1.5742 **	0.1945%
Labor	0.4400	−5.8556	0.8692	−0.0191	0.0107	1.7255 **	25.4186%

Note: $Z = a \times b/\sqrt{a^2\sigma_b{}^2 + b^2\sigma_a{}^2}$, where c represents the regression coefficient of artificial intelligence on the level of servitization in manufacturing; a represents the regression coefficient of artificial intelligence on the mediating variable; b represents the regression coefficient of the mediating variable on the level of servitization in manufacturing; and σ_a and σ_b represent the standard deviations of the corresponding estimated coefficients; Mediation Effect Proportion = $a \times b/c$, ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively, with robust standard errors clustered at the industry level in parentheses.

5. Further Discussion: Embedded Service Transformation and Blended Service Transformation

Embedded service transformation primarily involves integrating resources of both products and services, thereby moving products from the lower end to the higher end of the value chain. As a result, the main products involved in embedded transformation exhibit a strategic matching relationship with the original products throughout the value chain. Conversely, blended service transformation primarily extends into higher-value service sectors to explore new sources of profit growth.

To investigate the distinct effects of artificial intelligence on these two transformation modes, this study employs a fuzzy matching process to combine the Guo-Qian An CS-

MAR listed company database for the period 2005–2015 with the previously mentioned industrial-enterprise-customs merged data. The study filters out companies that reported service revenue in their annual reports for a minimum of two years, yielding a sample of 97 companies comprising 276 observations.

The corresponding econometric model is formulated as follows:

$$Service_{fit} = \beta_0 + \beta_1 AI_{it} + \beta_2 control_{fit} + \delta_f + \eta_t + \varepsilon_{fit} \quad (5)$$

In the equation, the variable "*Service*" represents the degree of manufacturing servitization, encompassing two distinct types: embedded and blended servitization. The level of embedded servitization (Embedded) is quantified as the proportion of revenue generated from embedded services, such as product distribution, product installation, after-sales maintenance, testing, recycling, remote monitoring, engineering consulting, energy efficiency, logistics consulting, IT solutions, etc., to the total operating revenue. Similarly, the level of blended servitization (Mixed) is assessed based on the percentage of revenue derived from blended services, such as futures brokerage, engineering services, property leasing, property management, department stores, trade, catering, and tourism, etc., out of the total operating revenue. The explanations for other variables remain consistent with the previous descriptions.

The regression results presented in Table 5 demonstrate a significant positive impact of artificial intelligence on embedded service transformation, whereas its influence on blended service transformation remains inconclusive. This suggests that artificial intelligence frequently extends the value chain of enterprises by incorporating activities like research and development, after-sales support, and technical services. As a result, it facilitates the advancement of their manufacturing servitization level. Similarly, motivated by artificial intelligence technology, enterprises exhibit a relatively modest inclination to reconfigure resource elements and expand their business scope. Additionally, this outcome underscores the significance of achieving coopetition (cooperation and competition) throughout the value chain, as it enables the mastery of core capabilities and the sharing of global benefits. Moreover, it further emphasizes the pivotal role played by artificial intelligence in the ongoing wave of industrial transformation and upgrading.

Table 5. The results of the manufacturing industry's transformation into a service-oriented mode.

Variables	Embedded (1)	Mixed (2)
AI	7.9885 *	−2.5489
	(4.5169)	(1.6471)
Control variable	Yes	Yes
Constant	2.0194 ***	0.0304
	(0.4129)	(0.0299)
Enterprise fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	276	276
R-squared	0.7926	0.5319

Note: *** and * respectively indicate 1% and 10% statistical significance, with industry-level clustering-robust standard errors in parentheses.

6. Conclusions and Policy Implications

As information technology advances rapidly, manufacturing enterprises are facing an urgent need to transition from being product suppliers to becoming comprehensive solution providers. The emergence of artificial intelligence technology further accelerates this transformation. This paper utilizes the 2018 version of OECD-ICIOT industry data and micro-matched data from customs and industrial enterprise databases to calculate the level of manufacturing servitization at the enterprise level from 2005 to 2015. Subsequently, it investigates the impacts of artificial intelligence on manufacturing servitization in China.

The research findings indicate that artificial intelligence significantly promotes manufacturing servitization, primarily through mechanisms such as improving enterprise TFP and optimizing labor structure. Additionally, the study reveals that artificial intelligence has a significant promoting effect on the transformation of embedded services, while its impact on blended service transformation is not evident.

The present study holds significant theoretical and practical implications. On the theoretical front, this study extends the enterprise domestic value-added analysis framework proposed by Kee and Tang [50] to the realm of manufacturing servitization. It establishes a theoretical analytical framework that reflects the constraints of artificial intelligence inputs and labor skill inputs. Based on this framework, the study explores the theoretical mechanisms through which artificial intelligence influences the servitization of the manufacturing industry by impacting enterprise total factor productivity and optimizing labor skill structures within a general equilibrium framework.

On the practical level, this study provides accurate measurements of the level of manufacturing servitization at the firm level, taking into account the differentiation between domestic and foreign sources of factor inputs. Consequently, it offers micro-level evidence of how artificial intelligence influences manufacturing servitization. Building upon this evidence, the study further distinguishes between embedded services and mixed services within the realm of manufacturing servitization, thereby clarifying the differentiated effects of different types of servitization transformations. This serves as valuable guidance for manufacturing enterprises to fully leverage artificial intelligence as a cutting-edge technology for achieving servitization transformation and making appropriate adjustments based on specific types of servitization transformations.

The conclusions drawn from this research have important policy implications. Firstly, it is crucial to provide strong support for the development of the artificial intelligence industry by strengthening the infrastructure and innovation platform, thereby promoting the deep integration of artificial intelligence with the manufacturing sector and other real economy sectors. This integration facilitates the transformation and upgrading of manufacturing enterprises. Secondly, increasing investment in worker education and skills training is essential to enable low-skilled workers to enhance their capabilities and adapt to the new landscape of manufacturing servitization, thereby reducing the potential employment impact resulting from the advancement of artificial intelligence in the manufacturing sector. Thirdly, actively leveraging artificial intelligence technology to promote intelligent matching and efficient collaboration between services and production factors can accelerate the pace of manufacturing servitization. Fourthly, expanding the positive impact of artificial intelligence is necessary to ensure its full potential in relatively underdeveloped regions, labor-intensive industries, private enterprises, processing trade enterprises, and hybrid-service-oriented businesses, fostering balanced development.

Finally, the present research in this paper still has some limitations. For example, since the latest customs data has not been disclosed in recent years, public data is available only up to 2015. At the same time, the measurement of the level of artificial intelligence development has been limited to industry-level analysis, failing to capture more granular results. Therefore, in future research, we will continuously update the data obtained and attempt to measure the level of artificial intelligence development at the enterprise level, aiming to conduct more in-depth and timely studies.

Author Contributions: Conceptualization, D.C. and H.X.; methodology, G.Z.; writing—all authors. All authors have read and agreed to the published version of the manuscript.

Funding: The work was supported by the National Social Science Foundation of China [21FJLB007, 22VRC172]; the State Ministry of Science and Technology, of Foreign Expert Category, Project [G2022160010L]. The authors gratefully acknowledge the helpful comments from anonymous referees.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

This paper expands upon the framework introduced by Kee and Tang [50] that focuses on firms exporting domestic value-added, and extends it to the domain of manufacturing servitization. By integrating this framework with the artificial intelligence technology model presented by Acemoglu and Restrepo [19], the paper investigates, within a unified analytical framework, the impact of artificial intelligence on the extent of manufacturing servitization.

Assuming that the production function of the firm satisfies:

$$Y_{ft} = A_{ft} K_{ft}^{\alpha} L_{ft}^{\beta} M_{ft}^{\lambda} \tag{A1}$$

In the table, the enterprise at time t is represented by f and t, respectively. The total factor productivity (TFP) of the enterprise is denoted as A. The capital, labor, and intermediate input of the enterprise are represented by K, L, and M, with their corresponding average prices indicated as r, ω, and P^{M}, respectively. The output elasticity of capital, labor, and intermediate input is represented by α, β, and λ, respectively, satisfying the condition $\alpha + \beta + \lambda = 1$.

Based on the research conducted by Acemoglu and Restrepo [19], it is clear that the adoption of artificial intelligence significantly enhances the total factor productivity of enterprises. This conclusion has been supported by other scholars, including Graetz and Michaels [18] and Aghion et al. [51]. Therefore, it can be inferred that:

$$\frac{\partial A_{ft}}{\partial AI_{ft}} > 0 \tag{A2}$$

Based on the findings of Kee and Tang [50], it has been determined that the intermediate input (M) in enterprises comprises two components: domestic intermediate input (M^D) and imported intermediate input (M^I), each associated with corresponding average prices (P^D and P^I, respectively). Therefore, the function representing the intermediate input can be expressed as:

$$M_{ft} = \left(M_{ft}^{D\frac{\kappa-1}{\kappa}} + M_{ft}^{I\frac{\kappa-1}{\kappa}} \right)^{\frac{\kappa}{\kappa-1}} \tag{A3}$$

In this context, κ represents the elasticity of substitution between domestic intermediate goods and imported intermediate goods, with $\kappa > 1$. The prices of intermediate goods can be expressed using a constant elasticity of substitution (CES) function of P^D and P^I, known as:

$$\mathrm{P}_{\mathrm{ft}}^{\mathrm{M}} = \left(\left(\mathrm{P}_{\mathrm{ft}}^{\mathrm{D}} \right)^{1-\kappa} + \left(\mathrm{P}_{\mathrm{ft}}^{\mathrm{I}} \right)^{1-\kappa} \right)^{\frac{1}{1-\kappa}} \tag{A4}$$

According to the principle of profit maximization or cost minimization, the firm can establish the following relationship:

$$C_{ft}\left(r_{ft}, \omega_{ft}, P_{ft}^{D}, P_{ft}^{I}, Y_{ft} \right) = \frac{Y_{ft}}{A_{ft}} \left(\frac{r_t}{\alpha} \right)^{\alpha} \left(\frac{\omega_{ft}}{\beta} \right)^{\beta} \left(\frac{P_{ft}^{M}}{\lambda} \right)^{\lambda} \tag{A5}$$

$$\frac{P_{ft}^{M} M_{ft}}{C_{ft}} = \lambda \tag{A6}$$

At this point, the marginal cost of the final product produced by the firm is:

$$c_{ft} = \frac{\partial C_{fi}}{\partial Y_{ft}} = \frac{1}{A_{ft}}(\frac{r_{ft}}{\alpha})^{\alpha}(\frac{\omega_{ft}}{\beta})^{\beta}(\frac{P^{M}{}_{ft}}{\lambda})^{\lambda} \tag{A7}$$

Referring to the study by Kee and Tang [50], assume that the share of imported intermediate goods in the total revenue of the firm is denoted as ϑ:

$$\vartheta = \frac{P^{I}_{ft}M^{I}_{ft}}{P_{ft}Y_{ft}} = \frac{P^{I}_{ft}M^{I}_{ft}}{P^{M}_{ft}M_{ft}}\frac{P^{M}_{ft}M_{ft}}{C_{ft}}\frac{C_{ft}}{P_{ft}Y_{ft}} = \lambda\frac{1}{\mu_{ft}}\frac{P^{I}_{ft}M^{I}_{ft}}{P^{M}_{ft}M_{ft}} \tag{A8}$$

The parameter μ represents the cost markup of the firm, which satisfies the condition $\mu = P/c$, where P is the price of the final good. By referring to the constraint function in Equation (A9), we can derive the proportion of the cost of imported intermediate goods to the total cost of raw materials, as illustrated in Equation (A11).

$$\min\ P^{I}_{ft}M^{I}_{ft} + P^{D}_{ft}M^{D}_{ft} \tag{A9}$$

$$s.t.\ M_{ft} = \left(M^{D\frac{\kappa-1}{\kappa}}_{ft} + M^{I\frac{\kappa-1}{\kappa}}_{ft}\right)^{\frac{\kappa}{\kappa-1}} \tag{A10}$$

$$\frac{P^{I}_{ft}M^{I}_{ft}}{P^{M}_{ft}M_{ft}} = \frac{1}{1+\left(P^{I}_{ft}/P^{D}_{ft}\right)^{\kappa-1}} \tag{A11}$$

Therefore, the Domestic Value-Added Rate (DVAR) for the enterprise can be expressed as:

$$DVAR_{ft} = 1 - \frac{P^{I}_{ft}M^{I}_{ft}}{P_{ft}Y_{ft}} = 1 - \lambda\frac{1}{\mu_{ft}}\frac{1}{1+\left(P^{I}_{ft}/P^{D}_{ft}\right)^{\kappa-1}} \tag{A12}$$

Similarly, the Foreign Value-Added Rate (FVAR) for the enterprise can be expressed as:

$$FVAR_{ft} = 1 - DVAR_{ft} = \lambda\frac{1}{\mu_{ft}}\frac{1}{1+\left(P^{I}_{ft}/P^{D}_{ft}\right)^{\kappa-1}} \tag{A13}$$

Following Deng et al. [48], the manufacturing servitization function can be expressed as:

$$Servitization_{ft} = DVAR_{ft}\theta_1 + FVAR_{ft}\theta_2 \tag{A14}$$

In the manufacturing industry, θ_1 and θ_2 indicate the proportions of domestic and foreign service value-added, respectively, relative to the overall domestic and foreign value-added. Specifically for China, the value-added rate of domestic services in the manufacturing sector surpasses the foreign value-added rate, denoted as $\theta_1 > \theta_2$. Therefore,

$$Servitization_{ft} = DVAR_{ft}(\theta_1 - \theta_2) + \theta_2 = \left[1 - \lambda\frac{1}{P_{ft}A_{ft}}\left(\frac{r_{ft}}{\alpha}\right)^{\alpha}\left(\frac{\omega_{ft}}{\beta}\right)^{\beta}\left(\frac{P^{M}_{ft}}{\lambda}\right)^{\lambda}\frac{1}{1+\left(P^{I}_{ft}/P^{D}_{ft}\right)^{\kappa-1}}\right](\theta_1 - \theta_2) + \theta_2 \tag{A15}$$

Taking the partial derivative of the total factor productivity A, we obtain:

$$\frac{\partial Servitization_{ft}}{\partial A_{ft}} = (\theta_1 - \theta_2)\frac{\lambda}{P_{ft}}\left(\frac{r_{ft}}{\alpha}\right)^{\alpha}\left(\frac{\omega_{ft}}{\beta}\right)^{\beta}\left(\frac{P^{M}_{ft}}{\lambda}\right)^{\lambda}A^{-2}_{ft} \tag{A16}$$

Therefore, the impact of artificial intelligence on manufacturing servitization can be expressed as:

$$\frac{\partial \mathrm{Servitization_{ft}}}{\partial \mathrm{AI_{ft}}} = \frac{\partial \mathrm{Servitization_{ft}}}{\partial \mathrm{A_{ft}}} \frac{\partial \mathrm{A_{ft}}}{\partial \mathrm{AI_{ft}}} \tag{A17}$$

According to Equations (A2) and (A16), $\frac{\partial \mathrm{Servitization_{ft}}}{\partial \mathrm{A_{ft}}} > 0$, $\frac{\partial \mathrm{A_{ft}}}{\partial \mathrm{AI_{ft}}} > 0$. Therefore, $\frac{\partial \mathrm{Servitization_{ft}}}{\partial \mathrm{AI_{ft}}} > 0$.

To gain a deeper understanding of the labor structure, we explore the implications of artificial intelligence investment on the framework of the labor market. We assume that a firm's labor input (L) consists of both low-skilled labor (L^u) and high-skilled labor (L^s), with the proportion of low-skilled labor represented by σ. Building upon the research conducted by Krusell et al. [52] and Lankisch et al. [53], we propose a significant substitutive relationship between a firm's artificial intelligence input (AI) and low-skilled labor (L^u), while high-skilled labor (L^s) remains non-substitutable. In this context, the firm's labor input L is characterized by the following function:

$$L_{ft} = \left[(1-\sigma)\left(L^s_{ft}\right)^{\gamma} + \sigma\left(AI_{ft} + L^u_{ft}\right)^{\gamma}\right]^{\frac{1}{\gamma}} \tag{A18}$$

where γ represents the elasticity of substitution between high-skilled labor and low-skilled labor, satisfying γ ∈ (0,1). In this case, the average price of labor can be expressed as a constant elasticity of substitution (CES) function of wages for high-skilled ω^s and low-skilled (ω^u) labor, along with the cost of artificial intelligence technology investment (P^{AI}):

$$\omega_{ft} = \left((1-\sigma)\left(\omega^s_{ft}\right)^{\frac{\gamma}{\gamma-1}} + \sigma\left(\omega^u_{ft}\right)^{\frac{\gamma}{\gamma-1}} + \sigma\left(P^{AI}_{ft}\right)^{\frac{\gamma}{\gamma-1}}\right)^{\frac{\gamma-1}{\gamma}} \tag{A19}$$

In a perfectly competitive market, the rental rate r for physical capital K is its marginal output, and therefore satisfies:

$$r_{ft} = \frac{\partial P_{ft} Y_{ft}}{\partial K_{ft}} = P_{ft} A_{ft} \alpha K^{\alpha-1}_{ft} L^{\beta}_{ft} M^{\lambda}_{ft} \tag{A20}$$

The rental price P^{AI} for artificial intelligence is given by:

$$P^{AI}_{ft} = \frac{\partial P_{ft} Y_{ft}}{\partial AI_{ft}} = P_{ft} A_{ft} K^{\alpha}_{ft} \beta L^{\beta-1}_{ft} \frac{1}{\gamma} \frac{L_{ft}}{L^r_{ft}} \sigma\gamma\left(AI_{ft} + L^u_{ft}\right)^{\gamma-1} M^{\lambda}_{ft} \tag{A21}$$

In a state of factor market equilibrium, there are no arbitrage opportunities that exist between different forms of capital. However, if such opportunities were present, capital would flow between traditional physical capital and artificial intelligence capital until equilibrium is achieved. This equilibrium condition is satisfied when the rate of return on capital (r) equals the price of artificial intelligence capital (P^{AI}).

By combining Equations (A20) and (A21), we obtain:

$$\alpha = K_{ft} \beta L^{-\gamma}_{ft} \sigma\left(AI_{ft} + L^u_{ft}\right)^{\gamma-1} \tag{A22}$$

$$\lambda = 1 - K_{ft}\beta\left[(1-\sigma)\left(L^s_{ft}\right)^{\gamma} + \sigma\left(AI_{ft} + L^u_{ft}\right)^{\gamma}\right]^{-1} \sigma\left(AI_{ft} + L^u_{ft}\right)^{\gamma-1} - \beta \tag{A23}$$

Similarly, in a perfectly competitive market, wages are equal to their marginal product. Therefore, we can determine:

$$\omega^s_{ft} = \frac{\partial P_{ft} Y_{ft}}{\partial L^s_{ft}} = P_{ft} A_{ft} K^{\alpha}_{ft} \frac{\beta}{\gamma}\left[(1-\sigma)\left(L^s_{ft}\right)^{\gamma} + \sigma\left(AI_{ft} + L^u_{ft}\right)^{\gamma}\right]^{\frac{\beta-\gamma}{\gamma}} (1-\sigma)\gamma\left(L^s_{ft}\right)^{\gamma-1} M^{\lambda}_{ft} \tag{A24}$$

$$\omega^u_{ft} = \frac{\partial P_{ft}Y_{ft}}{\partial L^u_{ft}} = P_{ft}A_{ft}K^{\alpha}_{ft}\frac{\beta}{\gamma}\left[(1-\sigma)\left(L^s_{ft}\right)^{\gamma} + \sigma\left(AI_{ft}+L^u_{ft}\right)^{\gamma}\right]^{\frac{\beta-\gamma}{\gamma}}\sigma\gamma\left(AI_{ft}+L^u_{ft}\right)^{\gamma-1}M^{\lambda}_{ft} \tag{A25}$$

$$\frac{\omega^s_{ft}}{\omega^u_{ft}} = \frac{1-\sigma}{\sigma}\left(\frac{L^s_{ft}}{AI_{ft}+L^u_{ft}}\right)^{\gamma-1} \tag{A26}$$

At this point, the relationship among human capital AI, low-skilled labor input L^u, and high-skilled labor input L^s satisfies:

$$\frac{L^s_{ft}}{AI_{ft}+L^u_{ft}} = \left(\frac{\omega^s_{ft}}{\omega^u_{ft}}\frac{\sigma}{1-\sigma}\right)^{\frac{1}{\gamma-1}} \tag{A27}$$

$$\lambda = 1 - K_{ft}\beta\left[(1-\sigma)\left(AI_{ft}+L^u_{ft}\right)^{\gamma}\left(\frac{\omega^s_{ft}}{w^u_{ft}}\frac{\sigma}{1-\sigma}\right)^{\frac{\gamma}{\gamma-1}} + \sigma\left(AI_{ft}+L^u_{ft}\right)^{\gamma}\right]^{-1}\sigma\left(AI_{ft}+L^u_{ft}\right)^{\gamma-1} - \beta \tag{A28}$$

Taking into account the two different labor input structures of low-skilled and high-skilled labor, the manufacturing servitization function can be further adjusted to:

$$\begin{aligned} Servitization_{ft} &= \left[1-\lambda\frac{1}{\mu_{ft}}\frac{1}{1+\left(P^I_{ft}/P^D_{ft}\right)^{\kappa-1}}\right](\theta_1-\theta_2)+\theta_2 \\ &= (\theta_1-\theta_2)-(\theta_1-\theta_2)\frac{1}{\mu_{ft}}\frac{1}{1+\left(P^I_t/P^D_t\right)^{\kappa-1}}\left\{1-K_{ft}\beta\left[(1-\lambda)\left(AI_{ft}+L^u_{ft}\right)^{\gamma}\left(\frac{\omega^s_{ft}}{\omega^u_{ft}}\frac{\lambda}{1-\lambda}\right)^{\frac{\gamma}{\gamma-1}}+\sigma\left(AI_{ft}+L^u_{ft}\right)^{\gamma}\right]^{-1}\sigma\left(AI_{ft}+L^u_{ft}\right)^{\gamma-1}-\beta\right\}+\theta_2 \end{aligned} \tag{A29}$$

Therefore, taking the partial derivative with respect to low-skilled labor, we obtain:

$$\begin{aligned} \frac{\partial Servitization_{ft}}{\partial L^u_{ft}} = -(\theta_1-\theta_2) \quad & \frac{1}{\mu_{ft}}\frac{1}{1+\left(P^I_{ft}/P^D_{ft}\right)^{\kappa-1}}\left\{K_{ft}\beta\left[(1-\sigma)\left(AI_{ft}+L^u_{ft}\right)^{\gamma}\left(\frac{\omega^s_{ft}}{\omega^u_{ft}}\frac{\sigma}{1-\sigma}\right)^{\frac{\gamma}{\gamma-1}}+\sigma\left(AI_{ft}+L^u_{ft}\right)^{\gamma}\right\}^{-2}\left[(1-\sigma)\gamma\left(\frac{\omega^s_{ft}}{\omega^u_{ft}}\frac{\sigma}{1-\sigma}\right)^{\frac{\gamma}{\gamma-1}}\left(AI_{ft}+L^u_{ft}\right)^{\gamma-1}\right. \\ & \left.+\gamma\sigma\left(AI_{ft}+L^u_{ft}\right)^{\gamma-1}\right]\sigma\left(AI_{ft}+L^u_{ft}\right)^{\gamma-1}-K_{ft}\beta\left[(1-\sigma)\left(AI_{ft}+L^u_{ft}\right)^{\gamma}\left(\frac{\omega^s_{ft}}{\omega^u_{ft}}\frac{\sigma}{1-\sigma}\right)^{\frac{\gamma}{\gamma-1}}+\sigma\left(AI_{ft}+L^u_{ft}\right)^{\gamma}\right]^{-1}\sigma(\gamma-1)\left(AI_{ft}+L^u_{ft}\right)^{\gamma-2}\right\} \end{aligned} \tag{A30}$$

Therefore, it is evident that $\frac{\partial Servitization_{ft}}{\partial L^u_{ft}} < 0$. Building upon the previous assumption, there exists a significant substitutive relationship between artificial intelligence capital (AI) and low-skilled labor L^u, i.e., $\frac{\partial L^u_{ft}}{\partial AI_{ft}} < 0$. As a result, we can conclude that $\frac{\partial Servitization_{ft}}{\partial L^u_{ft}} < 0$.

References

1. Yun, J.J.; Liu, Z.; Zhao, X. Introduction: Ambidextrous Open Innovation in the 4th Industrial Revolution. *Sci. Technol. Soc.* **2021**, *26*, 183–200. [CrossRef]
2. Kim, M.; Lim, C.; Hsuan, J. From Technology Enablers to Circular Economy: Data-Driven Understanding of the Overview of Servitization and Product–Service Systems in Industry 4.0. *Comput. Ind.* **2023**, *148*, 103908. [CrossRef]
3. Kumar, L.; Sharma, R.K. Exploring Research Issues and Potential Future Directions in Industry 4.0 Adoption in SMEs: A Comprehensive Analysis and Integration. *FIIB Bus. Rev.* **2023**, 23197145231203512. [CrossRef]
4. Meindl, B.; Ayala, N.F.; Mendonça, J.; Frank, A.G. The Four Smarts of Industry 4.0: Evolution of Ten Years of Research and Future Perspectives. *Technol. Forecast. Soc. Change* **2021**, *168*, 120784. [CrossRef]
5. Gupta, M.; Jauhar, S.K. Digital Innovation: An Essence for Industry 4.0. *Thunderbird Int. Bus. Rev.* **2023**, *65*, 279–292. [CrossRef]
6. Stadlmann, C.; Berend, G.; Fratrič, A.; Szántó, Z.; Aufreiter, D.; Ueberwimmer, M.; Mang, S. Find Me If You Can! Identification of Services on Websites by Human Beings and Artificial Intelligence. In *Marketing and Smart Technologies*; Reis, J.L., López, E.P., Moutinho, L., Santos, J.P.M.D., Eds.; Smart Innovation, Systems and Technologies; Springer Nature: Singapore, 2022; Volume 279, pp. 23–35. ISBN 9789811692673.
7. Abou-Foul, M.; Ruiz-Alba, J.L.; López-Tenorio, P.J. The Impact of Artificial Intelligence Capabilities on Servitization: The Moderating Role of Absorptive Capacity—A Dynamic Capabilities Perspective. *J. Bus. Res.* **2023**, *157*, 113609. [CrossRef]
8. Nicoletti, B.; Appolloni, A. Artificial Intelligence for the Management of Servitization 5.0. *Sustainability* **2023**, *15*, 11113. [CrossRef]
9. Tang, G.; Mai, H. How Does Manufacturing Intelligentization Influence Innovation in China from a Nonlinear Perspective and Economic Servitization Background? *Sustainability* **2022**, *14*, 14032. [CrossRef]
10. Leone, D.; Schiavone, F.; Appio, F.P.; Chiao, B. How Does Artificial Intelligence Enable and Enhance Value Co-Creation in Industrial Markets? An Exploratory Case Study in the Healthcare Ecosystem. *J. Bus. Res.* **2021**, *129*, 849–859. [CrossRef]

11. Burström, T.; Parida, V.; Lahti, T.; Wincent, J. AI-Enabled Business-Model Innovation and Transformation in Industrial Ecosystems: A Framework, Model and Outline for Further Research. *J. Bus. Res.* **2021**, *127*, 85–95. [CrossRef]
12. Von Garrel, J.; Jahn, C. Design Framework for the Implementation of AI-Based (Service) Business Models for Small and Medium-Sized Manufacturing Enterprises. *J. Knowl. Econ.* **2023**, *14*, 3551–3569. [CrossRef]
13. Sjödin, D.; Parida, V.; Palmié, M.; Wincent, J. How AI Capabilities Enable Business Model Innovation: Scaling AI through Co-Evolutionary Processes and Feedback Loops. *J. Bus. Res.* **2021**, *134*, 574–587. [CrossRef]
14. Waltersmann, L.; Kiemel, S.; Stuhlsatz, J.; Sauer, A.; Miehe, R. Artificial Intelligence Applications for Increasing Resource Efficiency in Manufacturing Companies—A Comprehensive Review. *Sustainability* **2021**, *13*, 6689. [CrossRef]
15. Fernald, J.G.; Jones, C.I. The Future of US Economic Growth. *Am. Econ. Rev.* **2014**, *104*, 44–49. [CrossRef]
16. Acemoglu, D.; Restrepo, P. Robots and Jobs: Evidence from US Labor Markets. *J. Political Econ.* **2020**, *128*, 2188–2244. [CrossRef]
17. Wang, Y.; Li, Y. Chinese Economic Growth and Sustainable Development: Role of Artificial Intelligence and Natural Resource Management. *Resour. Policy* **2023**, *85*, 103996. [CrossRef]
18. Graetz, G.; Michaels, G. Robots at Work. *Rev. Econ. Stat.* **2018**, *100*, 753–768. [CrossRef]
19. Acemoglu, D.; Restrepo, P. The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *Am. Econ. Rev.* **2018**, *108*, 1488–1542. [CrossRef]
20. Agrawal, A.; Gans, J.S.; Goldfarb, A. Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *J. Econ. Perspect.* **2019**, *33*, 31–50. [CrossRef]
21. Agrawal, A.; Gans, J.; Goldfarb, A.; National Bureau of Economic Research (Eds.) *The Economics of Artificial Intelligence: An Agenda*; National Bureau of Economic Research Conference Report; The University of Chicago Press: Chicago, IL, USA; London, UK, 2019; ISBN 978-0-226-61347-5.
22. Prettner, K.; Strulik, H. Innovation, Automation, and Inequality: Policy Challenges in the Race against the Machine. *J. Monet. Econ.* **2020**, *116*, 249–265. [CrossRef]
23. Acemoglu, D.; Restrepo, P. The Wrong Kind of AI? Artificial Intelligence and the Future of Labour Demand. *Camb. J. Reg. Econ. Soc.* **2020**, *13*, 25–35. [CrossRef]
24. Abubakar, A.M.; Behravesh, E.; Rezapouraghdam, H.; Yildiz, S.B. Applying Artificial Intelligence Technique to Predict Knowledge Hiding Behavior. *Int. J. Inf. Manag.* **2019**, *49*, 45–57. [CrossRef]
25. Choi, D.Y.; Kang, J.H. Net Job Creation in an Increasingly Autonomous Economy: The Challenge of a Generation. *J. Manag. Inq.* **2019**, *28*, 300–305. [CrossRef]
26. Feng, A.; Graetz, G. Training Requirements, Automation, and Job Polarisation. *Econ. J.* **2020**, *130*, 2249–2271. [CrossRef]
27. Makarius, E.E.; Mukherjee, D.; Fox, J.D.; Fox, A.K. Rising with the Machines: A Sociotechnical Framework for Bringing Artificial Intelligence into the Organization. *J. Bus. Res.* **2020**, *120*, 262–273. [CrossRef]
28. Hémous, D.; Olsen, M. The Rise of the Machines: Automation, Horizontal Innovation, and Income Inequality. *Am. Econ. J. Macroecon.* **2022**, *14*, 179–223. [CrossRef]
29. Qi, Y.; Mao, Z.; Zhang, M.; Guo, H. Manufacturing Practices and Servitization: The Role of Mass Customization and Product Innovation Capabilities. *Int. J. Prod. Econ.* **2020**, *228*, 107747. [CrossRef]
30. Shen, L.; Sun, C.; Ali, M. Role of Servitization, Digitalization, and Innovation Performance in Manufacturing Enterprises. *Sustainability* **2021**, *13*, 9878. [CrossRef]
31. Kowalkowski, C.; Gebauer, H.; Kamp, B.; Parry, G. Servitization and Deservitization: Overview, Concepts, and Definitions. *Ind. Mark. Manag.* **2017**, *60*, 4–10. [CrossRef]
32. Hofacker, C.; Golgeci, I.; Pillai, K.G.; Gligor, D.M. Digital Marketing and Business-to-Business Relationships: A Close Look at the Interface and a Roadmap for the Future. *Eur. J. Mark.* **2020**, *54*, 1161–1179. [CrossRef]
33. Rymaszewska, A.; Helo, P.; Gunasekaran, A. IoT Powered Servitization of Manufacturing—An Exploratory Case Study. *Int. J. Prod. Econ.* **2017**, *192*, 92–105. [CrossRef]
34. Dai, Y.; Zhao, X.; Yang, J.; Chen, H. How Does Manufacturing Servitization Effect Global Value Chain Upgrading? Tests Based on the Dual Perspectives of "Participation" and "Division Position". *Econ. Anal. Policy* **2024**, *81*, 709–723. [CrossRef]
35. Huang, G.; Ma, L.; Xietian, Z.; Huang, X. Servitization of Manufacturing and China's Power Status Upgrading of Global Value Network. *Struct. Change Econ. Dyn.* **2024**, *68*, 313–328. [CrossRef]
36. Zhang, J. Impact of Manufacturing Servitization on Factor Productivity of Industrial Sector Using Global Value Chain. *Sustainability* **2022**, *14*, 5354. [CrossRef]
37. Hu, Y.; Sun, S.; Jiang, M.; Dai, Y. Research on the Promoting Effect of Servitization on Export Technological Sophistication of Manufacturing Enterprises. *PLoS ONE* **2021**, *16*, e0255891. [CrossRef]
38. Fang, M.; Yang, R. Research on Effects of Input Servitization on Export Technological Complexity of Manufacturing Industry of China. *Des. Autom. Embed. Syst.* **2018**, *22*, 279–291. [CrossRef]
39. Martín-Peña, M.-L.; Sánchez-López, J.-M.; Díaz-Garrido, E. Servitization and Digitalization in Manufacturing: The Influence on Firm Performance. *J. Bus. Ind. Mark.* **2019**, *35*, 564–574. [CrossRef]
40. Brax, S.A.; Calabrese, A.; Levialdi Ghiron, N.; Tiburzi, L.; Grönroos, C. Explaining the Servitization Paradox: A Configurational Theory and a Performance Measurement Framework. *Int. J. Oper. Prod. Manag.* **2021**, *41*, 517–546. [CrossRef]
41. Martinez, V.; Neely, A.; Velu, C.; Leinster-Evans, S.; Bisessar, D. Exploring the Journey to Services. *Int. J. Prod. Econ.* **2017**, *192*, 66–80. [CrossRef]

42. Visnjic, I.; Ringov, D.; Arts, S. Which Service? How Industry Conditions Shape Firms' Service-Type Choices. *J. Prod. Innov. Manag.* **2019**, *36*, 381–407. [CrossRef]
43. Kohtamäki, M.; Parida, V.; Oghazi, P.; Gebauer, H.; Baines, T. Digital Servitization Business Models in Ecosystems: A Theory of the Firm. *J. Bus. Res.* **2019**, *104*, 380–392. [CrossRef]
44. Paiola, M.; Schiavone, F.; Grandinetti, R.; Chen, J. Digital Servitization and Sustainability through Networking: Some Evidences from IoT-Based Business Models. *J. Bus. Res.* **2021**, *132*, 507–516. [CrossRef]
45. Paschou, T.; Rapaccini, M.; Adrodegari, F.; Saccani, N. Digital Servitization in Manufacturing: A Systematic Literature Review and Research Agenda. *Ind. Mark. Manag.* **2020**, *89*, 278–292. [CrossRef]
46. Chen, S.; Zhang, H. Does Digital Finance Promote Manufacturing Servitization: Micro Evidence from China. *Int. Rev. Econ. Finance* **2021**, *76*, 856–869. [CrossRef]
47. Li, H.; Chu, L.; Qin, X. Analysis of the Factors Affecting China's Manufacturing Servitization from the Perspective of the Ecological Environment. *Sustainability* **2023**, *15*, 2934. [CrossRef]
48. Deng, Y.; Rong, C.; Chen, R. Does Manufacturing Servitization Reduce Emissions Intensity? Evidence from China. *Appl. Econ.* **2023**, 1–16. [CrossRef]
49. Díaz-Mora, C.; Gandoy, R.; González-Díaz, B. Looking into Global Value Chains: Influence of Foreign Services on Export Performance. *Rev. World Econ.* **2018**, *154*, 785–814. [CrossRef]
50. Kee, H.L.; Tang, H. Domestic Value Added in Exports: Theory and Firm Evidence from China. *Am. Econ. Rev.* **2016**, *106*, 1402–1436. [CrossRef]
51. Aghion, P.; Antonin, C.; Bunel, S. Artificial Intelligence, Growth and Employment: The Role of Policy. *Econ. Stat. Econ. Stat.* **2020**, *510–512*, 149–164. [CrossRef]
52. Krusell, P.; Ohanian, L.E.; Rios-Rull, J.-V.; Violante, G.L. Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis. *Econometrica* **2000**, *68*, 1029–1053. [CrossRef]
53. Lankisch, C.; Prettner, K.; Prskawetz, A. How Can Robots Affect Wage Inequality? *Econ. Model.* **2019**, *81*, 161–169. [CrossRef]
54. Pereira, V.; Hadjielias, E.; Christofi, M.; Vrontis, D. A Systematic Literature Review on the Impact of Artificial Intelligence on Workplace Outcomes: A Multi-Process Perspective. *Hum. Resour. Manag. Rev.* **2023**, *33*, 100857. [CrossRef]
55. Jabeur, R.; Boujoudar, Y.; Azeroual, M.; Aljarbouh, A.; Ouaaline, N. Microgrid Energy Management System for Smart Home Using Multi-Agent System. *Int. J. Electr. Comput. Eng. IJECE* **2022**, *12*, 1153. [CrossRef]
56. Brandt, L.; Van Biesebroeck, J.; Zhang, Y. Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing. *J. Dev. Econ.* **2012**, *97*, 339–351. [CrossRef]
57. Crinò, R.; Ogliari, L. Financial Imperfections, Product Quality, and International Trade. *J. Int. Econ.* **2017**, *104*, 63–84. [CrossRef]
58. Decker, R.; Haltiwanger, J.; Jarmin, R.; Miranda, J. The Role of Entrepreneurship in US Job Creation and Economic Dynamism. *J. Econ. Perspect.* **2014**, *28*, 3–24. [CrossRef]
59. Coad, A.; Segarra, A.; Teruel, M. Innovation and Firm Growth: Does Firm Age Play a Role? *Res. Policy* **2016**, *45*, 387–400. [CrossRef]
60. Paiola, M.; Gebauer, H. Internet of Things Technologies, Digital Servitization and Business Model Innovation in BtoB Manufacturing Firms. *Ind. Mark. Manag.* **2020**, *89*, 245–264. [CrossRef]
61. Falkenreck, C.; Wagner, R. From Managing Customers to Joint Venturing with Customers: Co-Creating Service Value in the Digital Age. *J. Bus. Ind. Mark.* **2022**, *37*, 643–656. [CrossRef]
62. Figueroa-Armijos, M. Does Public Entrepreneurial Financing Contribute to Territorial Servitization in Manufacturing and KIBS in the United States? *Reg. Stud.* **2019**, *53*, 341–355. [CrossRef]
63. Manova, K.; Wei, S.-J.; Zhang, Z. Firm Exports and Multinational Activity Under Credit Constraints. *Rev. Econ. Stat.* **2015**, *97*, 574–588. [CrossRef]
64. Chen, Z.; Li, Y.; Zhang, J. The Bank–Firm Relationship: Helping or Grabbing? *Int. Rev. Econ. Financ.* **2016**, *42*, 385–403. [CrossRef]
65. Eapen, A.; Yeo, J.; Sasidharan, S. Finance Constraints and Technology Spillovers from Foreign to Domestic Firms. *Econ. Model.* **2019**, *76*, 50–62. [CrossRef]
66. Liu, Q.; Qiu, L.D.; Zhan, C. Trade Liberalization and Domestic Vertical Integration: Evidence from China. *J. Int. Econ.* **2019**, *121*, 103250. [CrossRef]