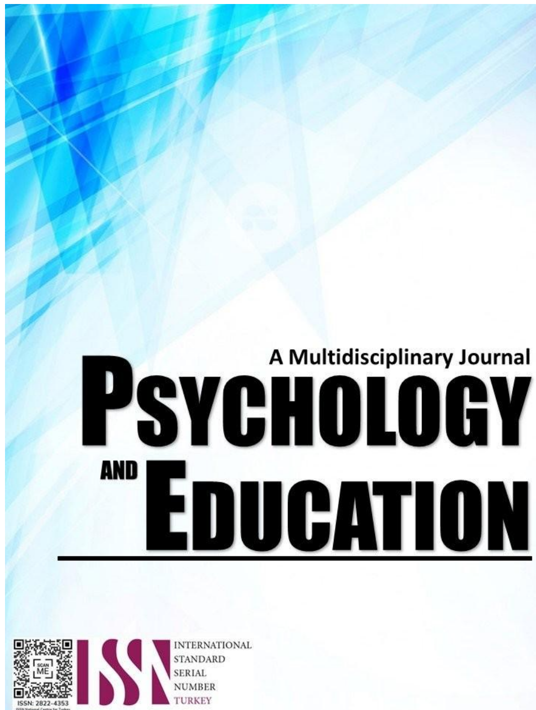
IMPACT OF DIGITAL TECHNOLOGIES ON PRODUCTION CHARACTERISTICS OF AUTOMOTIVE PARTS MANUFACTURERS IN HUBEI, CHINA



PSYCHOLOGY AND EDUCATION: A MULTIDISCIPLINARY JOURNAL

Volume: 50
Issue 3
Pages: 327-338
Document ID: 2025PEMJ4865
DOI: 10.70838/pemj.500309
Manuscript Accepted: 11-12-2025

Psych Educ, 2025, **50**(3): 327-338, Document ID:2025PEMJ4865, doi:10.70838/pemj.500309, ISSN 2822-4353
Research Article

Impact of Digital Technologies on Production Characteristics of Automotive Parts Manufacturers in Hubei, China

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Abstract

Competition in the automotive industry drives companies to reduce costs, accelerate development, and enhance processes. Digital technologies play a central role in meeting these demands. This study examines the impact of digital tools on the production practices of automotive parts manufacturers in Hubei Province, China, with a focus on assemblers, mechanics, and machine operators. Using a quantitative, descriptive-correlational design, the research surveyed 374 factory workers. Findings show that digital technology is moderately used, with core systems such as real-time production control and ERP well established; however, adoption of mobile and shop-floor technologies is lower. Production methods combine traditional mass production with growing capabilities for complex and customized orders. The use of digital technology is strongly linked to improved production characteristics, especially for machine operators. Unfortunately, the impact varies by role and is less pronounced for mechanics. These results suggest that tailored, role-specific technologies, rather than generic solutions, are most effective in achieving full digital integration and productivity gains. By highlighting the need for targeted digital strategies, this study offers valuable guidance for manufacturers aiming to compete in the evolving global market.

Keywords: *digital technology, production characteristics, automotive parts, production control, automation*

Introduction

Recent advances in digital technology have revolutionized the manufacturing industries worldwide, particularly in the automotive sector. The integration of automation, the Internet of Things (IoT), artificial intelligence (AI), and digital twins, collectively known as Industry 4.0, has created new opportunities to enhance efficiency, quality, and flexibility in production processes. These innovations enable manufacturers to optimize workflows, predict maintenance needs, and tailor products to meet evolving consumer demands. For example, IoT devices enable real-time monitoring and analytics, while AI applications automate defect detection, improving yield and accelerating production cycles.

The integration of digital technologies in manufacturing environments has become a defining characteristic of modern industrial transformation, often referred to as the Fourth Industrial Revolution or Industry 4.0. These technologies, including the Internet of Things (IoT), Artificial Intelligence (AI), advanced robotics, cyber-physical systems (CPS), and digital twins, are reshaping how factories operate, influencing production efficiency, flexibility, and customization capabilities (Rashid & Kausik, 2025). As manufacturing firms adopt these innovations, they undergo profound changes in their production characteristics, including improved process optimization, reduced downtime, and enhanced product quality.

Digitalization in factories enables the collection and analysis of real-time data, supporting predictive maintenance and informed decision-making (Javaid et al., 2024). For example, IoT devices can continuously monitor machine health and performance, enabling predictive maintenance that minimizes unplanned downtime and extends equipment lifespan (Zhong et al., 2023). Moreover, the use of AI and machine learning in production lines facilitates the detection of anomalies and optimization of workflows, reducing waste and increasing throughput (Balan et al., 2025).

The impact of digital technologies also extends to production flexibility and customization. Intelligent manufacturing systems can respond dynamically to changing demand patterns and production requirements, supporting mass customization without sacrificing efficiency (Wang, 2020). Additionally, digital twins — virtual replicas of physical systems — enable simulation and testing in a risk-free digital environment, allowing manufacturers to optimize designs and processes before implementation (Soori et al., 2023). However, while digitalization offers significant benefits, it also presents challenges. High initial investment costs, cybersecurity risks, and the need for workforce upskilling persist as barriers to widespread adoption (Xiao et al., 2024). Empirical studies consistently demonstrate that factory digital transformation leads to measurable improvements in key production metrics, including lead times, production costs, and output quality (Li et al., 2025).

Despite these benefits, many automotive factories face significant barriers to full digital integration, including high investment costs, cybersecurity concerns, and the need for advanced worker skills. In China, Hubei Province has become a hub for automotive parts manufacturing, with numerous enterprises adopting digital technologies to strengthen competitiveness. However, most factories remain in a transitional phase: core systems, such as ERP and real-time production control, are established, but mobile and shop-floor technologies are less developed.

While digitalization offers measurable improvements in production, its adoption and impact are uneven across different roles, including assemblers, mechanics, and machine operators. There is a lack of clarity about how digital technologies specifically influence production characteristics and about the gaps that hinder complete digital transformation at the operational level. This study addresses the need to understand role-based differences in technology adoption. It aims to identify targeted strategies for achieving integrated, responsive, and efficient manufacturing within the automotive parts sector of Hubei Province.

Methodology

Research Design

This study employed a quantitative descriptive-correlational research design. According to Sirisilla (2023), a descriptive quantitative research design systematically collects and analyzes numerical data to accurately and objectively describe the characteristics, frequencies, trends, and categories of a population or phenomenon. This approach was chosen to systematically describe the current state of digital technology adoption and production characteristics and determine the nature and strength of the relationship.

Respondents

The study was conducted in three automotive parts manufacturing enterprises in Shiyan City, Hubei Province, China. Shiyan City, known as "China's Commercial Vehicle Capital," is a significant automotive production base with a highly developed industrial cluster. The selected companies are: Shiyan Laian Auto Parts Co., LTD., whose main products are air and oil filters, Shiyan Dongfeng Fudian Automotive Electric Co., LTD., whose main products are automotive harness and safety belts, and Shiyan Judi Metal Pipe Industry Co., LTD., whose main products are automotive oil and gas pipe fittings. These companies were selected to integrate technology into their production processes and provide the researcher with access to their data.

Furthermore, the study's population comprised 548 factory workers from the three companies directly involved in manufacturing. The Raosoft sample size calculator determined a minimum sample size of 374 respondents. The final sample consisted of 374 participants, comprising assemblers (n=182), mechanics (n=129), and machine operators (n=63).

Table 1. *Lists the sample sizes of the three enterprises*

Company	*Assemblers*	*Mechanics*	*Machine Operators*	*Total*
Shiyan Laian Auto Parts Co., LTD., Company	61	43	21	125
Shiyan Dongfeng Fudian Automotive Electric Co., LTD。	58	42	20	120
Shiyan Judi Metal Pipe Industry Co., LTD.	63	44	22	129
Total	182	129	63	374

Procedure

The research instrument was a structured questionnaire adapted from the work of M. Đukić Mijatović et al. (2020). The questionnaire was designed to measure two primary constructs: the extent of digital technology use in the factory and the prevailing production characteristics of the manufacturing firms.

To ensure its validity, the questionnaire has been validated by professionals in the field and through research. Additionally, the questionnaire underwent pilot testing, yielding an overall Cronbach's alpha of 0.892, which is considered acceptable.

On the other hand, each company's management sought permission via a formal letter. Upon approval, a QR code linking to the online survey was created and distributed to the factory employees, with assistance from company managers and colleagues. The online form included an informed consent questionnaire to ensure that participants' participation was voluntary and informed. Data collection was monitored until the target sample size was reached.

Data Analysis

Data were analyzed using the Statistical Package for the Social Sciences (SPSS). SPSS is used in the study for its robust capabilities to organize, analyze, and interpret large datasets generated from survey responses and production metrics. The software enables efficient processing of quantitative data through descriptive statistics and inferential statistics, which are essential for determining relationships and testing hypotheses about digital technology adoption and production characteristics in manufacturing environments.

Descriptive statistics, including frequency, percentage, weighted mean, and standard deviation, were used to summarize the demographic profiles and assess the levels of digital technology adoption and production characteristics. Additionally, inferential statistics, such as the regression analysis, were employed to determine the effect of digital technologies on production characteristics.

Ethical Considerations

Informed consent was obtained from all participants prior to completing the questionnaire. The participation was entirely voluntary, and respondents could withdraw at any time without penalty. All data collected was kept confidential, used solely for research purposes, and anonymized to protect privacy. Only the researchers had access to the raw data, which will be appropriately discarded one year after the study's completion. Finally, no conflicts of interest were identified in this study.

Results and Discussion

Table 2. *Company Profile*

Company Profile		*N*	*%*
Type of Ownership	Private	148	33.64
	Government	145	32.95
	Mixed (private and government or joint stock)	147	33.41
	Total	440	100
Capitalization	Less than or equal to 10,000,000 RMB (micro)	82	18.64
	10,000,000 to less than 50,000,000 RMB (small)	133	30.23
	50,000,000 to less than 200,000,000 RMB (medium)	127	28.86
	200,000,000 to less than 1,000,000,000 RMB (large)	75	17.05
	1,000,000,000 RMB or more (super large)	23	5.23
	Total	440	100
No. of years in Business	1 year to less than 5 years	98	22.27
	5 years to less than 10 years	180	40.91
	10 years to less than 15 years	108	24.55
	15 years or more	54	12.27
	Total	440	100

Table 2 presents the basic characteristics of 440 sample enterprises across three dimensions: type of ownership, Capitalization, and Number of Years in Business. The distribution is presented through the actual sample size and percentages.

Type of ownership: The proportions of private, government, and mixed enterprises are 33.64%, 32.95%, and 33.41% respectively, with the proportions being relatively balanced, covering enterprises with different ownership structures, providing a foundation for subsequent analysis of the impact of ownership differences on the application of digital technologies and production models (for example, government enterprises may pay more attention to norms, while private enterprises may be more flexible).

Capitalization: The majority are small- and medium-sized enterprises, with a combined share of 59.09% for those with values of 100 million to 500 million and 500 million to 2 billion. Large-scale enterprises (over 1 billion) account for only 5.23%, which aligns with the automotive parts industry status in Hubei Province, where small and medium-sized supporting enterprises dominate. The capital scale may affect the enterprise's ability to invest in digital technologies (for example, large-scale enterprises are more likely to bear the cost of high-end technologies).

No. of years in Business: The enterprises with a 5–10-year operating period have the highest proportion (40.91%), mature enterprises with more than 15 years account for 12.27%, and new enterprises with 1 - 5 years account for 22.27%. The distribution of different operating years can support the analysis of the correlation between the enterprise's development stage and the accumulation of digital technologies and the maturity of the production model (for example, mature enterprises may have a more stable technical system, while new enterprises may be more likely to introduce new technologies).

Table 3. *Digital Technologies in the factory as assessed by Assemblers*

Digital Technologies in factory	*Assemblers*							
		NE	*ME*	*E*	*VE*	*WM*	*Std. Dev.*	*Verbal Interpretation*
1.Mobile/wireless devices for programming and controlling facilities and machinery (e.g., tablets) are used in the factory	f	8	95	66	15	2.48	0.71	Moderately Evident
	%	4.35	51.63	35.87	8.15			
2. Use of Digital solutions to provide drawings, work schedules, or work instructions directly on the shop floor	f	11	76	80	17	2.56	0.74	Moderately Evident
	%	5.98	41.30	43.48	9.24			
3. Use of software for production planning and Scheduling (ERP system)	f	10	71	73	30	2.67	0.81	Moderately Evident
	%	5.44	38.59	39.67	16.30			
4. Use of Digital supply chain management	f	6	73	69	36	2.73	0.81	Moderately Evident
	%	3.26	39.67	37.50	19.57			
5. Use of near real-time production control system (e.g., systems of centralized operating and machine data acquisition	f	5	74	77	28	2.70	0.76	Moderately Evident
	%	2.72	40.22	41.85	15.21			
6. Use of Systems for automation and management of internal logistics (e.g., RFID)	f	10	84	68	22	2.55	0.77	Moderately Evident
	%	5.43	45.65	36.96	11.96			
7. Use of Product lifecycle management systems	f	12	82	70	20	2.53	0.77	Moderately Evident
	%	6.52	44.57	38.04	10.87			
8. Use of Virtual Reality or simulation for product design or product development	f	10	78	70	26	2.61	0.80	Moderately Evident
	%	5.44	42.39	38.04	14.13			

Table 3 records the assessment results of 182 assembly workers on eight factory digital technologies, including the frequency, percentage, weighted average (out of 1-4 points, with higher scores indicating more obvious application), standard deviation, and verbal explanations for different application levels (not obvious, relatively blatant, apparent, pronounced). The weighted average o f the eight technologies ranges from 2.48 to 2.73, and the verbal explanations are all "fairly obvious", indicating that the assem bly workers perceive that factory digital technologies have been widely applied, but have not reached a highly mature stage.

The highest scores are "Digital Supply Chain Management" (2.73) and "Near Real-Time Production Control System" (2.70), which are closely related to the scenarios in the assembly workers' work involving material connection and production rhythm control, r eflecting the practicality of these technologies in the assembly process; the lower score is "Product Lifecycle Management System" (2.53), possibly because the assembly workers rarely participate in the complete lifecycle management of products, and have a w eaker perception of this technology. Meanwhile, the standard deviation ranges from 0.71 to 0.81, indicating that the assembly workers' judgments on the applicability of each technology are highly consistent and that the data are reliable.

The findings suggest that, although the factory has established a foundational digital infrastructure, it is currently in a t ransitional stage rather than a fully mature state of digital integration. The "moderately evident" assessment from assemblers suggests that while they interact with these technologies, the systems are not yet seamlessly embedded into their core workflows to the point of being indispensable. This aligns with studies on Industry 4.0 adoption, which indicate that the most significant challenge is often not the acquisition of technology but its deep integration with human capital and existing processes (Khan et al., 2024). Therefore, a significant opportunity exists for management to enhance worker training and refine workflows to move beyond partial implementation, unlocking the full productivity and efficiency potential these digital tools promise.

Table 4. *Digital Technologies in the factory as assessed by Mechanics*

Digital Technologies in factory		*Mechanics*						
		NE	*ME*	*E*	*VE*	*WM*	*Std. Dev.*	*Verbal Interpretation*
1.Mobile/wireless devices for programming and controlling facilities and machinery (e.g., tablets) are used in the factory	f	14	67	67	26	2.60	0.84	Moderately Evident
	%	8.05	38.51	38.51	14.93			
2. Use of Digital solutions to provide drawings, work schedules, or work instructions directly on the shop floor	f	15	69	61	29	2.60	0.87	Moderately Evident
	%	8.62	39.66	35.06	16.66			
3. Use of software for production planning and Scheduling (ERP system)	f	19	69	57	29	2.55	0.90	Moderately Evident
	%	10.91	39.66	32.76	16.67			
4. Use of Digital supply chain management	f	22	67	54	31	2.54	0.93	Moderately Evident
	%	12.64	38.51	31.03	17.82			
5. Use of near real-time production control system (e.g., systems of centralized operating and machine data acquisition	f	20	63	59	32	2.59	0.92	Moderately Evident
	%	11.49	36.21	33.91	18.39			
6. Use of Systems for automation and management of internal logistics (e.g., RFID)	f	24	61	60	29	2.54	0.93	Moderately Evident
	%	13.79	35.06	34.48	16.67			
7. Use of Product lifecycle management systems	f	17	74	49	34	2.57	0.91	Moderately Evident
	%	9.77	42.53	28.16	19.54			
8. Use of Virtual Reality or simulation for product design or product development	f	33	57	59	25	2.44	0.96	Moderately Evident
	%	5.44	42.39	38.04	14.13			

Table 4 presents evaluations of 129 mechanics of eight factory digital technologies, using the same indicators as in Table 3. The weighted average ranges from 2.44 to 2.60, indicating a level of "Moderately Evident". The overall application level is similar to that assessed by assemblers, but slightly lower than the ratings they gave for some technologies (such as digital supply chain management).

The scores for "Real-time Production Control System" (2.59) and "Product Lifecycle Management System" (2.57) are relatively high, matching the job attributes of mechanics in equipment maintenance and lifecycle management. The "Virtual Reality or Simulation" score is the lowest (2.44), possibly because the mechanics focused more on equipment operation and maintenance and less on virtual technology applications during the product design stage. While the standard deviation ranges from 0.84 to 0.96, slightly hi gher than the assessment by assemblers, indicating that the judgment differences in the degree of technology application by mechanics a re slightly larger. This might be due to differences in the depth and breadth of technology contact for mechanics' positions compared to those of assemblers.

The results imply that a one-size-fits-all approach to digitalization is insufficient and that technology must be tailored to the specific functions of different roles. The fact that mechanics rate their technology use as "moderately evident," slightly lower than assemblers, suggests that the current tools may be better suited for routine production tasks than for the complex, diagnostic nature of maintenance work. This is supported by their higher valuation of "Product Lifecycle Management Systems," which are critical for long-term machine health. According to Javaid et al. (2022), the success of Industry 4.0 hinges on the Task-Technology Fit principle, in which tools are specifically chosen and adapted to enhance the specific activities of the user group. Therefore, the organization should invest in specialized digital tools for mechanics, such as predictive maintenance dashboards and mobile diagnostic apps, to better support their unique workflows and elevate technology adoption from moderate to fully integrated.

Table 5. *Digital Technologies in the factory as assessed by Machine Operators*

Digital Technologies in factory		*Machine Operators*						
		NE	*ME*	*E*	*VE*	*WM*	*Std. Dev.*	*Verbal Interpretation*
1.Mobile/wireless devices for programming and controlling facilities and machinery (e.g., tablets) are used in the factory	f	5	47	20	10	2.43	0.79	Moderately Evident
	%	6.10	57.32	24.39	12.19			
2. Use of Digital solutions to provide drawings, work schedules, or work instructions directly on the shop floor	f	7	43	24	8	2.40	0.78	Moderately Evident
	%	8.54	52.44	29.27	9.75			
3. Use of software for production planning and Scheduling (ERP system)	f	6	28	31	17	2.72	0.88	Moderately Evident
	%	7.32	34.15	37.80	20.73			
4. Use of Digital supply chain management	f	7	31	31	13	2.61	0.86	Moderately Evident
	%	8.54	37.80	37.81	15.85			
5. Use of near real-time production control system (e.g., systems of centralized operating and machine data acquisition	f	6	31	30	15	2.66	0.86	Moderately Evident
	%	7.32	37.80	36.59	18.29			
6. Use of Systems for automation and management of internal logistics (e.g., RFID)	f	9	27	27	19	2.68	0.95	Moderately Evident
	%	10.98	32.93	32.92	23.17			
7. Use of Product lifecycle management systems	f	5	29	33	15	2.70	0.84	Moderately Evident
	%	6.10	57.32	24.39	12.19			
8. Use of Virtual Reality or simulation for product design or product development	f	6	33	35	8	2.55	0.77	Moderately Evident
	%	7.32	40.24	42.68	9.76			

Table 5 presents evaluations of 63 machine operators on eight factory digital technologies, using the same indicators as before. The weighted average values range from 2.40 to 2.72, indicating a level of "Moderately Evident". The overall application level is consistent with the assessment trends of assemblers and mechanics.

The "Production Planning and Scheduling Software (ERP System)" received the highest score (2.72), as the work of machine operators directly relies on production plans and interacts frequently with the ERP system; the "System for Automating and Managing Internal Logistics (such as RFID)" (2.68) and "Product Lifecycle Management System" (2.70) also received relatively high scores, reflecting the actual application of digital logistics and product management technologies in the machine operation process. The standard deviation ranges from 0.77 to 0.95, with "Automated Internal Logistics System" having the highest standard deviation (0.95), indicating that there are specific differences in the judgment of machine operators regarding the degree of application of this technology, possibly due to the significant differences in the level of logistics automation across different production lines.

The results for machine operators suggest that the factory's digital transformation is progressing unevenly, leading to inconsistencies in the operational environment. While the overall "Moderately Evident" rating aligns with other roles, the high standard deviation in systems like "Automated Internal Logistics" (0.95) is a critical finding. It suggests that some machine operators work with advanced, automated material handling, while others on different production lines may not, creating potential bottlenecks and process inefficiencies. According to the Smart Manufacturing Working Group (2022), a primary barrier to realizing the full potential of Industry 4.0 is the failure to achieve horizontal integration, resulting in "islands of automation." Therefore, management should prioritize standardizing the application of core technologies across all production lines to create a cohesive, efficient, and truly integrated innovative factory system.

Table 6 presents the overall assessment of 8 digital technologies by 374 respondents (assemblers, mechanics, and machine operators combined), with the same indicators as before. The weighted average ranges from 2.52 to 2.65, all indicating "Moderately Evident", consistent with the individual assessment results for each position. This indicates that the overall application of digital technologies in the factory is at the "moderately widespread" stage. The "Near Real-Time Production Control System" (2.65) and "Production Planning and Scheduling Software (ERP System)" (2.63) received the highest scores, reflecting that enterprises have a relatively good digital foundation in production monitoring and planning, and these two technologies are the core supports of the production process; "Mobile/Wireless Equipment Control" (2.52) received the lowest score, possibly because front-line operations still rely more on traditional equipment, and the popularity of wireless control technology needs to be improved. The standard deviation ranges from 0.78 to 0.87, indicating high overall consistency, suggesting that perceptions of the degree of application of digital technologies across different positions are relatively uniform and that data stability is strong.

The overall findings suggest that the enterprise has successfully established a robust digital foundation for centralized planning and monitoring, but faces a critical gap in extending that digitalization to frontline execution. The high ERP and real-time production systems scores indicate a mature IT backbone. However, the low adoption of mobile/wireless controls suggests that shop floor operations remain comparatively traditional. This creates a disconnect that can limit operational agility and data-driven decision-making. According to Tanane et al. (2025), achieving true digital maturity requires bridging this gap between top-floor systems and shop-floor practices. Therefore, the strategic priority should be to empower workers with accessible mobile tools to complete the data loop between planning and execution, unlocking the full potential of a truly connected and responsive manufacturing environment.

Table 6. *Digital Technologies in the factory, as assessed by overall*

Digital Technologies in factory		*Overall*						
		NE	*ME*	*E*	*VE*	*WM*	*Std. Dev.*	*Verbal Interpretation*
1.Mobile/wireless devices for programming and controlling facilities and machinery (e.g., tablets) are used in the factory	f	27	209	153	51	2.52	0.78	Moderately Evident
	%	6.14	47.50	34.77	11.59			
2. Use of Digital solutions to provide drawings, work schedules, or work instructions directly on the shop floor	f	33	188	165	54	2.55	0.80	Moderately Evident
	%	7.50	42.7	37.50	12.27			
3. Use of software for production planning and Scheduling (ERP system)	f	35	168	161	76	2.63	0.86	Moderately Evident
	%	7.95	38.18	36.59	17.28			
4. Use of Digital supply chain management	f	35	171	154	80	2.63	0.87	Moderately Evident
	%	7.95	38.86	35.00	18.19			
5. Use of near real-time production control system (e.g., systems of centralized operating and machine data acquisition	f	31	168	166	75	2.65	0.84	Moderately Evident
	%	7.05	38.18	37.73	17.04			
6. Use of Systems for automation and management of internal logistics (e.g., RFID)	f	43	172	155	70	2.57	0.87	Moderately Evident
	%	9.77	39.09	35.23	15.91			
7. Use of Product lifecycle management systems	f	34	185	152	69	2.58	0.84	Moderately Evident
	%	7.73	42.05	34.55	15.67			
8. Use of Virtual Reality or simulation for product design or product development	f	49	168	154	59	2.53	0.87	Moderately Evident
	%	11.14	38.18	37.27	13.41			

Table 7 records the evaluations of 182 Assemblers on 12 production characteristics (such as order-driven mode, batch size, and product complexity), and the indicators are consistent with the digital technology assessment. The weighted average is between 2.60 and 2.77, indicating "Moderately Evident", which reflects that the production characteristics perceived by the assembly workers have a clear tendency.

The ratings for "producing automotive components for inventory" (2.77) and "producing using standard procedures without customer specifications" (2.72) are the highest, indicating that in the assembly process, inventory production and standardized production mode are more prominent; the rating for "designing the production process to manufacture single automotive components" (2.60) is the lowest, reflecting that the assembly process is more inclined towards batch production rather than single-piece customization. The ratings for "production of complex automotive components" (2.66) and "production of medium-complex components" (2.65) are close, indicating that the assembly workers believe that the enterprise has a particular ability to adapt to product complexity, with medium complexity being the primary focus.

Table 7. *Production Characteristics as assessed by Assemblers*

Production Characteristics		*Assemblers*						
		NE	*ME*	*E*	*VE*	*WM*	*Std. Dev.*	*Verbal Interpretation*
1. Product development according to customers' specification is used.	f	11	62	90	21	2.66	0.76	Moderately Evident
	%	5.98	33.70	48.91	11.41			
2. Standardized basic program incorporating customer-specific options is used for manufacturing automotive parts.	f	10	58	93	23	2.70	0.76	Moderately Evident
	%	5.43	31.52	50.55	12.50			
3. Standard program is used in production process of automotive parts without customers' specification.	f	16	57	73	38	2.72	0.89	Moderately Evident
	%	8.70	30.98	39.67	20.65			
4. Production of automotive parts are on a made-to-order basis	f	10	68	78	28	2.67	0.80	Moderately Evident
	%	5.43	36.96	42.39	15.22			
5. Automotive parts are processed on an assembly-to-order basis.	f	10	72	78	24	2.63	0.78	Moderately Evident
	%	5.43	39.13	42.40	13.04			
6. Automotive parts are produced are for stock purposes	f	9	62	75	38	2.77	0.83	Moderately Evident
	%	4.89	33.70	40.76	20.65			
7. Production process is designed to manufacture single unit automotive parts.	f	12	71	79	22	2.60	0.78	Moderately Evident
	%	6.52	38.59	42.93	11.96			
8. Production process is designed to manufacture small or medium batches of automotive parts.	f	9	68	87	20	2.64	0.74	Moderately Evident
	%	4.89	36.96	47.28	10.87			
9. Production process is designed to manufacture	f	9	61	81	33	2.75	0.80	Moderately Evident

large batches of automotive parts.	%	4.89	33.15	44.03	17.93			
10. The company's production process can accommodate production of simple automotive parts.	f	11	68	79	26	2.65	0.80	Moderately Evident
	%	5.98	36.96	42.93	14.13			
11. The company's production process can accommodate production of automotive parts with medium complexity.	f	13	67	76	28	2.65	0.82	Moderately Evident
	%	7.07	36.41	41.30	15.22			
12. The company's production process can accommodate production of complex automotive parts.	f	12	62	87	23	2.66	0.78	Moderately Evident
	%	6.52	33.70	47.28	12.50			

The production characteristics reported by assemblers suggest that the company employs a flexible manufacturing strategy, ble nding mass production with mass customization. The high ratings for standardized, inventory-based production indicate a core focus on efficiency and economies of scale. However, this is well complemented by a strong capability to produce medium- and high-complexity components, suggesting the system is designed to handle variety. This approach aligns with the principles of modern manuf acturing, in which firms must balance cost efficiency with the ability to respond to diverse market demands (Habib et al., 2023). The key implication is that the production system is not rigid; instead, it is strategically configured to leverage the stability of standardized processes while being agile enough to accommodate product complexity and variability, positioning the company competitively in a dynamic market.

Table 8 presents evaluations by 129 mechanics of 12 production characteristics, using the same indicators as before. The weighted average ranges from 2.63 to 3.10, with most being "Moderately Evident". Among them, "The production process is designed for mass production" (3.10) is the only one that is "very evident", reflecting that mechani cs strongly perceive that the enterprise operates mainly on a mass production model.

The ratings for "Producing automotive components for inventory" (2.98) and "Product development according to customer requirements" (2.87) are relatively high, indicating that mechanics believe that the enterprise focuses on inventory manageme nt and customer customization requirements while also pursuing large-scale production. "The company's production process can meet the production of simple automotive components" (2.63) has the lowest rating, possibly because mechanics have more exposure to medium- and higher-complexity production processes. The standard deviation ranges from 0.76 to 0.91, with good overall consistency. The standard deviation for evaluating "Mas production" is relatively low (0.88), indicating that mechanics have a high unifie d understanding of this characteristic.

Table 8. *Production Characteristics as assessed by Mechanics*

Production Characteristics		*Mechanics*						
		NE	*ME*	*E*	*VE*	*WM*	*Std. Dev.*	*Verbal Interpretation*
1. Product development according to customers' specification is used.	f	5	57	68	44	2.87	0.83	Moderately Evident
	%	2.87	32.76	39.08	25.29			
2. Standardized basic program incorporating customer-specific options is used for manufacturing automotive parts.	f	2	66	70	36	2.80	0.77	Moderately Evident
	%	1.15	37.93	40.23	20.69			
3. Standard program is used in production process of automotive parts without customers' specification.	f	6	62	47	59	2.91	0.91	Moderately Evident
	%	3.45	35.63	27.00	33.92			
4. Production of automotive parts are on a made-to-order basis	f	4	76	59	35	2.72	0.81	Moderately Evident
	%	2.30	43.68	33.91	20.11			
5. Automotive parts are processed on an assembly-to-order basis.	f	4	55	73	42	2.88	0.80	Moderately Evident
	%	2.30	31.61	41.95	24.14			
6. Automotive parts are produced are for stock purposes	f	5	57	49	63	2.98	0.90	Evident
	%	2.87	32.76	28.16	36.21			
7. Production process is designed to manufacture single unit automotive parts.	f	7	69	65	33	2.71	0.82	Moderately Evident
	%	4.02	39.66	37.36	18.96			
8. Production process is designed to manufacture small or medium batches of automotive parts.	f	6	75	65	28	2.66	0.79	Moderately Evident
	%	3.45	43.10	37.36	16.09			
9. Production process is designed to manufacture large batches of automotive parts.	f	7	39	58	70	3.10	0.88	Very Evident
	%	4.02	22.41	33.33	40.24			
10. The company's production process can accommodate production of simple automotive parts.	f	10	79	50	35	2.63	0.87	Moderately Evident
	%	5.69	45.46	28.74	20.11			
11. The company's production process can accommodate production of automotive parts with medium complexity.	f	1	61	73	39	2.86	0.76	Moderately Evident
	%	0.57	35.06	41.96	22.41			

12. The company's production process can accommodate production of complex automotive parts.	f	6	63	46	59	2.91	0.91	Moderately Evident
	%	3.45	36.21	26.44	33.90			

The mechanics' assessments strongly suggest that a dedicated mass production model underpins the company's competitive strategy, leveraging economies of scale. The unified, "Very Evident" rating for large-batch manufacturing clearly emphasizes high-volume output. Critically, the lower rating for producing simple parts suggests that the factory's processes and machinery are highly specialized and optimized for complex components, making them inefficient or ill-suited for less demanding or varied tasks. This operational model aligns with the "dedicated production line" concept on the Product-Process Matrix, prioritizing cost leadership in a stable, high-volume market (Deswal et al., 2024). The implication is that while the company is exceptionally efficient at its core production, this specialization may introduce process rigidity, posing a potential challenge if market demands were to shift towards greater product variety or smaller order sizes.

Table 9. *Production Characteristics as assessed by Machine Operators*

Production Characteristics	*Machine Operators*							
		NE	*ME*	*E*	*VE*	*WM*	*Std. Dev.*	*Verbal Interpretation*
1. Product development according to customers' specification is used.	f	1	30	32	19	2.84	0.79	Moderately Evident
	%	1.22	36.59	39.02	23.17			
2. Standardized basic program incorporating customer-specific options is used for manufacturing automotive parts.	f	0	37	28	17	2.76	0.78	Moderately Evident
	%							
3. Standard program is used in production process of automotive parts without customers' specification.	f	1	40	28	13	2.65	0.76	Moderately Evident
	%	1.22	48.78	34.15	15.85			
4. Production of automotive parts are on a made-to-order basis	f	2	29	28	23	2.88	0.85	Moderately Evident
	%	2.44	35.37	34.15	28.04			
5. Automotive parts are processed on an assembly-to-order basis.	f	1	21	36	24	3.01	0.78	Evident
	%	1.22	25.61	43.90	29.27			
6. Automotive parts are produced are for stock purposes	f	2	32	37	11	2.70	0.73	Moderately Evident
	%	2.44	39.02	45.12	13.42			
7. Production process is designed to manufacture single unit automotive parts.	f	3	31	29	19	2.78	0.85	Moderately Evident
	%	3.66	37.80	35.37	23.17			
8. Production process is designed to manufacture small or medium batches of automotive parts.	f	1	34	25	22	2.83	0.84	Moderately Evident
	%	1.22	41.46	30.49	26.83			
9. Production process is designed to manufacture large batches of automotive parts.	f	2	34	26	20	2.78	0.85	Moderately Evident
	%	2.44	41.46	31.71	24.39			
10. The company's production process can accommodate production of simple automotive parts.	f	2	30	32	18	2.80	0.81	Moderately Evident
	%	2.44	36.59	39.02	21.95			
11. The company's production process can accommodate production of automotive parts with medium complexity.	f	2	28	31	21	2.87	0.83	Moderately Evident
	%	2.44	34.15	37.80	25.61			
12. The company's production process can accommodate production of complex automotive parts.	f	1	30	32	19	2.84	0.79	Moderately Evident
	%	1.22	36.59	39.02	23.17			

Table 9 presents evaluations of 63 machine operators on 12 production characteristics, using the same indicators as before. The weighted average is between 2.65 and 3.01, with a majority of "Moderately Evident" results. Among them, "processing automotive components in an order-based assembly manner" (3.01) is "Evident", reflecting that machine operators have a strong perception of the order-driven assembly mode in the production execution process.

"Order-based production" (2.88) and "the production process is designed to manufacture automotive components in small batches" (2.83) have higher scores, indicating that machine operators believe that the production process has certain flexibility and can adapt to order demands and small-batch production; "producing using standard procedures without customer specifications" (2.65) has a relatively lower score, possibly because machine operators rely more on specific order instructions. The standard deviation ranges from 0.73 to 0.85, demonstrating good consistency. Machine operators have a relatively unified understanding of inventory production, primarily focused on "producing automotive components for inventory" (0.73).

Based on the machine operators' assessment, the factory's production process is strongly implied to be a responsive, order-driven system based on an Assemble-to-Order (ATO) model. The clear "Evident" rating for "processing automotive parts on an assembly-to-order basis," reinforced by high scores for small-batch and on-demand production, indicates a pull-system where actual customer orders, not forecasts, initiate work. This operational strategy is a deliberate choice to strike a balance between efficiency and flexibility. Cavero et al. (2025) outlined that an ATO strategy enables companies to offer customization and rapid response to customer needs by holding components in inventory and performing final assembly only when an order is placed. The implication is that the company prioritizes lean principles—such as minimizing finished goods inventory and reducing the risk of obsolescence—positioning itself as an agile player in a market that values customization and timely delivery.

Table 10. *Production Characteristics as assessed by Overall*

Production Characteristics		*Overall*						
		NE	*ME*	*E*	*VE*	*WM*	*Std. Dev.*	*Verbal Interpretation*
1. Product development according to customers' specification is used.	f	17	149	190	84	2.78	0.80	Moderately Evident
	%	3.86	33.86	43.18	19.10			
2. Standardized basic program incorporating customer-specific options is used for manufacturing automotive parts.	f	12	161	191	76	2.75	0.77	Moderately Evident
	%	2.73	36.59	43.41	17.27			
3. Standard program is used in production process of automotive parts without customers' specification.	f	23	159	148	110	2.78	0.88	Moderately Evident
	%	5.23	36.13	33.64	25.00			
4. Production of automotive parts are on a made-to-order basis	f	16	173	165	86	2.73	0.81	Moderately Evident
	%	3.64	39.31	37.50	19.55			
5. Automotive parts are processed on an assembly-to-order basis.	f	15	148	187	90	2.8	0.80	Moderately Evident
	%	3.41	33.64	42.50	20.45			
6. Automotive parts are produced are for stock purposes	f	16	151	161	112	2.84	0.85	Moderately Evident
	%	3.64	34.32	36.59	25.45			
7. Production process is designed to manufacture single unit automotive parts.	f	22	171	173	74	2.68	0.81	Moderately Evident
	%	5	38.86	39.32	16.82			
8. Production process is designed to manufacture small or medium batches of automotive parts.	f	16	177	177	70	2.68	0.78	Moderately Evident
	%	3.64	40.23	40.23	15.90			
9. Production process is designed to manufacture large batches of automotive parts.	f	18	134	165	123	2.89	0.86	Moderately Evident
	%	4.09	30.45	35.45	28.01			
10. The company's production process can accommodate production of simple automotive parts.	f	23	177	161	79	2.67	0.83	Moderately Evident
	%	5.23	40.23	36.59	17.95			
11. The company's production process can accommodate production of automotive parts with medium complexity.	f	16	156	180	88	2.77	0.81	Moderately Evident
	%	3.64	35.45	40.91	20			
12. The company's production process can accommodate production of complex automotive parts.	f	19	159	166	96	2.77	0.84	Moderately Evident
	%	4.32	36.14	37.73	21.81			

Table 10 presents the overall assessment of 12 production characteristics by 374 respondents, using the same indicators as before. The weighted average values range from 2.67 to 2.89, all indicating a level of "quite obvious". This overall reflects the commonalities in the production characteristics of enterprises, which are based on mass production (2.89), while also having specific customer orientation (developing products according to customer requirements, 2.78) and flexibility (assembly according to orders, 2.80).

The scores for "production process designed for mass production" (2.89) and "automobile parts produced are for inventory" (2.84) are the highest, which are in line with the large-scale production requirements of the automotive parts industry for supporting vehicle manufacturers; the scores for "production process designed for manufacturing single or small-batch automotive parts" (2.68) and "production process designed for manufacturing small-batch or medium-batch automotive parts" (2.68) are relatively low, indicating that enterprises still mainly rely on mass production. Single-piece and small-batch production capabilities need to be strengthened to meet market demand.

In the assessment of product complexity, the scores for "medium complexity" (2.77) and "complex" (2.77) are the same, higher than "simple" (2.67), reflecting that the production capacity of enterprises can adapt to components with mid-range and above complexity, which is in line with the technological upgrading trend of the industry.

The results imply that the company is actively managing a hybrid production strategy, strategically positioned between traditional mass production and modern mass customization. The strong scores for inventory-based and large-batch production highlight an apparent reliance on the efficiencies of a Make-to-Stock system. However, this is balanced by significant capabilities in handling on-demand orders and producing highly complex parts, indicating a move towards a more flexible, customer-centric model. This balancing act is a hallmark of companies evolving to meet the diverse needs of their markets. As argued by Tu (2001), the future of manufacturing lies in mastering mass customization by creating systems that deliver variety and personalization at a cost comparable to that of mass production. Therefore, the key implication is that the company's success hinges on its ability to continue integrating these two competing operational philosophies, leveraging its complex production capabilities to offer tailored solutions without sacrificing core efficiency.

Table 11. *Regression Results*

Variables	*Beta Coefficient*	*p-value*	*R-squared*	*Probability Level*	*Interpretation*
Assemblers Digital Technology and Production Characteristics	0.459	0.000	0.123	P<0.05	Significant Effect
Mechanics Digital Technology and Production Characteristics	0.168	0.000	0.111	P<0.05	Significant Effect
Machine Operators Digital Technology and Production Characteristics	0.526	0.000	0.420	P<0.05	Significant Effect
Overall Digital Technology and Production Characteristics	0.285	0.000	0.097	P<0.05	Significant Effect

This section analyzes and interprets the relationship between the adoption of digital technologies and the production characteristics of assemblers, mechanics, and machine operators, as presented in Table 10.

Assemblers: Digital Technology and Production Characteristics. The results presented in Table 11 indicate a strong, positive, and statistically significant effect of digital technologies on assemblers' production characteristics. This strong correlation suggests that as assemblers increase their use of digital tools, there is a corresponding and substantial improvement in their performance metrics, such as assembly speed, accuracy, and overall efficiency. The magnitude of the relationship implies that technologies such as augmented reality (AR) work instructions, collaborative robots, and digital quality control systems have a highly impactful effect on the structured and often repetitive tasks associated with assembly work.

The implications of this finding are significant for manufacturing industries. The results empirically support the Industry 4.0 framework, which posits that cyber-physical systems augment human capabilities. According to Moghaddam et al. (2021), digital tools such as AR overlays reduce workers' cognitive load by providing real-time guidance, thereby minimizing errors and accelerating the learning curve for complex assemblies. Furthermore, integrating robots enables human workers to focus on tasks that require dexterity and critical thinking, while offloading strenuous or repetitive motions, thereby increasing throughput and reducing physical strain (Javaid et al., 2022). This symbiotic relationship boosts productivity, enhances worker safety, and improves job satisfaction, making technology a strategic asset for optimizing assembly lines.

Mechanics: Digital Technology and Production Characteristics. For mechanics, Table 11 reveals a moderate, positive, and statistically significant effect of digital technology adoption on production characteristics. This result indicates that while digital tools are beneficial, their impact on mechanics' core production metrics is less pronounced than that of assemblers. The nature of a mechanic's work, which emphasizes diagnostics, problem-solving, and non-routine repairs, likely accounts for this more moderate correlation. Therefore, technology is more influential in enhancing the quality and accuracy of their work (e.g., through precision diagnostics) than in increasing the speed of manual repairs.

This finding suggests that the primary value of digital technology for mechanics lies in augmenting their diagnostic and decision-making skills. Modern diagnostic software, for instance, can rapidly parse vehicle data to pinpoint faults that would otherwise require hours of manual investigation, thereby improving first-time fix rates and customer satisfaction (Musser, 2024). Moreover, technologies such as remote assistance via AR glasses connect mechanics to a global pool of expertise, enabling them to tackle unfamiliar problems with confidence. This transforms the mechanic's role from a purely hands-on practitioner to a sophisticated technician who leverages data to solve complex mechanical issues (Younghusband, 2022). Therefore, strategic investment for this group should prioritize knowledge-based and diagnostic systems over tools that aim solely at task automation.

Machine Operators: Digital Technology and Production Characteristics. The analysis for machine operators shows the study's most potent effect, with a strong, positive, and highly significant relationship between digital technology and production characteristics. This influential association suggests that the role of a machine operator is fundamentally intertwined with digital systems. Integrating advanced Human-Machine Interfaces (HMIs), real-time performance monitoring, and predictive maintenance algorithms directly empowers operators to achieve higher output levels, precision, and machine uptime. For these workers, technology is not just an aid but a core component of their operational environment.

The implications of this result suggest a paradigm shift in the skill set required for machine operation. As machines become more intelligent and more connected, the operator's role evolves from manual control to oversight and optimization of the system (Shweta et al., 2025). Operators are now expected to interpret data from digital dashboards, make informed adjustments to production parameters, and collaborate with intelligent systems to prevent downtime. This trend supports the widespread call for upskilling the manufacturing workforce, where digital literacy and data analysis become essential competencies (Abdelfattah et al., 2025). Consequently, organizations that pair investments in innovative factory technology with robust training programs are best positioned to realize the full productivity benefits.

Overall Results for Digital Technology and Production Characteristics. Aggregating across all three groups, Table 11 demonstrates a strong, positive, and highly significant overall effect of digital technology adoption on production characteristics. This overarching finding confirms that digital technology is a critical driver of performance across roles in a production environment. Although the effect size varies depending on the specific demands of each job—with machine operators showing the highest integration and mechanics the most specialized application—the universal positive trend underscores the transformative impact of digitalization.

The key implication is that digital transformation is a fundamental and strategic imperative for any industrial or technical organization seeking a competitive edge. This result aligns with the broader economic theory of technological enablement, which pos its that new tools amplify human labor, thereby increasing productivity (Kassa & Worku, 2025). The varying correlation coefficients across the groups also highlight the importance of a tailored implementation strategy; a one-size-fits-all approach is suboptimal. Instead, organizations should deploy specific technologies that address the unique challenges and opportunities of each role—such as guided instruction for assemblers, diagnostic support for mechanics, or system optimization for operators. Ultimatel y, a strategic, role-specific adoption of digital tools is essential to unlocking new levels of efficiency and quality.

Conclusions

This study comprehensively analyzes digital technology adoption and its relationship with production characteristics in Hubei Province, China's automotive parts manufacturing sector. The findings conclusively show that the industry is in a critical transitional phase. While there is a foundational investment in core digital systems, such as ERP and real-time production monitoring, overall adoption is "moderately evident," suggesting the full potential of a mature digital ecosystem has not yet been realized. The production environment reflects this transition, operating as a hybrid model that strategically balances the cost efficiencies of mass production with the flexibility required for customization and complex, on-demand orders.

The most significant insight from this research is the strong, positive correlation between digitalization and production characteristics, which underscores that technology is a key enabler of modern manufacturing capabilities. However, this relationship is not uniform across the workforce. The impact of digital tools varies significantly by role, with machine operators experiencing the tightest integration and mechanics requiring more specialized, diagnostic-focused solutions. This variance highlights a critical challenge: the insufficient implementation of generic, top-down technology. The current disconnect between robust central planning systems and less-developed shop-floor tools creates operational friction, preventing the realization of a seamlessly connected smart factory. Ultimately, this study confirms that the journey toward Industry 4.0 is more complex than acquiring new technologies. It is a strategic endeavor that requires a deep understanding of the unique workflows and challenges faced by different workforce segments. The research highlights that true digital maturity is achieved not when technology is merely present, but when it is profoundly and cohesively integrated into the daily tasks of every worker, from the assembly line to the maintenance bay. For manufacturers in Hubei, bridging the gap between high-level data systems and front-line operational execution is the definitive next step in securing a competitive advantage.

Based on the findings, it is recommended that management prioritize a targeted and role-specific technology implementation strategy. Rather than broad, uniform investments, the company should focus on deploying specialized digital tools that address the distinct needs of each worker group: advanced diagnostic and remote assistance technologies for mechanics; augmented reality (AR) work instructions for assemblers; and standardized mobile controls for machine operators to ensure horizontal integration across all production lines. This technological push must be paired with a robust workforce upskilling program to move employees from passive users to active participants in a data-driven environment. Furthermore, strategic efforts should be made to bridge the gap between top-floor planning systems and shop-floor execution, creating a fully integrated, responsive, efficient, and innovative factory ecosystem.

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