APEM journal
Advances in Production Engineering & Management
Volume 20 | Number 4 | December 2025 | pp 529–545
https://doi.org/10.14743/apem2025.4.556
ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

How competitive pressures and technological innovations shape organizational practices: Insights from the European manufacturing survey

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A B S T R A C T

This study investigates the relationship between competitive pressures, technological adoption, and organizational dynamics in the manufacturing sector, with a focus on Serbian firms. Using data from the European Manufacturing Survey (EMS) of 146 manufacturing firms, Structural Equation Modeling (SEM) was employed to analyze the influence of competitive factors on the adoption of advanced manufacturing technologies, including Production Control Systems, Automation and Robotics, Efficiency Technologies, and Additive Manufacturing and Simulation Tools. The findings highlight the pivotal role of Production Control Systems in enhancing operational efficiency and strategic decision-making, demonstrating a significant positive effect on both the Organization of Production (β = 0.384, p = 0.001) and Production Management/Controlling (β = 0.500, p < 0.001). In contrast, other technologies did not show statistically significant effects, indicating more selective adoption patterns. Barriers such as financial constraints, technical complexity, and limited organizational readiness were found to restrict broader integration of automation, efficiency, and additive technologies. These results underscore that firms tend to prioritize technologies that offer immediate and auditable operational benefits. Practical implications include the need for workforce upskilling programs, managerial training in digital transformation, innovation hubs for lower-risk piloting, and supportive policy frameworks (e.g., financial incentives, regulatory sandboxes). Collectively, these measures can strengthen absorptive capacity, reduce resistance to change, and foster resilience, sustainability, and competitiveness through targeted technological integration and organizational alignment.

A R T I C L E I N F O

Keywords:
Competitive pressures;
Advanced manufacturing technologies;
Production Control Systems;
Efficiency Technologies;
Additive Manufacturing;
Structural Equation Modeling (SEM);
European Manufacturing Survey (EMS);
Serbian manufacturing sector

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Article history:
Received 9 January 2025
Revised 23 August 2025
Accepted 3 September 2025

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1. Introduction

The manufacturing industry faces increasing pressures from competitive markets, technological advancements, and sustainability demands. Recent disruptions, such as the COVID-19 pandemic, highlighted vulnerabilities in production systems [1, 2]. To address these challenges, firms must adapt by adopting innovative technologies and aligning their organizational strategies to ensure resilience and competitiveness.

Technological innovations such as production control systems, automation, additive manufacturing, and efficiency technologies, combined with concepts like multilayered agility and agile intrapreneurship [3-5], have been recognized as key enablers of operational improvement [6, 7].

These innovations contribute to reducing costs, improving customization, and enhancing sustainability. While previous research has extensively examined the benefits of these technologies, the interplay between competitive pressures, technology adoption, and organizational performance remains underexplored [8, 9].

A growing body of literature suggests that integrating technological advancements with organizational practices can optimize production processes and management efficiency [10, 11]. By leveraging production control mechanisms and sustainability-focused innovations, firms can create agile production systems capable of meeting evolving market demands [12, 13].

While agile maintenance and sustainable design approaches offer practical benefits, their interaction with competitive factors remains underexplored [14, 15]. Sustainable product design models, for example, significantly improve the alignment of environmental and social considerations with product quality, but their adoption in the face of competitive pressures is still insufficiently studied [15]. Similarly, agile maintenance strategies demonstrate potential for optimizing operational efficiency by minimizing downtime and aligning actions with the condition of equipment, yet their broader implications for organizational processes under competitive dynamics require further investigation [15, 16]. Despite the promise of these advancements, existing studies often neglect how competitive factors drive the adoption of specific technologies or influence their integration into organizational practices [17]. Moreover, comprehensive models that empirically examine these relationships in real-world manufacturing contexts—particularly in developing economies—are notably absent.

This study aims to address the following research questions:

- How do competitive factors (e.g., price, quality, customization) drive the adoption of technological innovations in manufacturing?
- How do these technologies impact organizational practices such as production control and management?

The objective of this study is to empirically analyze the relationships between competitive pressures, technological innovations, and organizational practices. Using data from the European Manufacturing Survey (EMS), this research applies Structural Equation Modeling (SEM) to validate hypothesized relationships [18, 19]. The findings aim to contribute to the literature by providing actionable insights for manufacturing firms seeking to enhance competitiveness and sustainability through strategic technological adoption and organizational alignment.

The structure of the study is as follows: A literature review is provided in Section 2, outlining the theoretical background and previous research relevant to the study. The research methodology is detailed in Section 3, including data collection procedures and the analytical framework used. The results are presented in Section 4, followed by a discussion of their theoretical and practical implications. Finally, the study is concluded in Section 5, summarizing key findings and suggesting directions for future research.

2. Literature review

2.1 Competitive factors: Catalysts of technological advancement in manufacturing

The manufacturing sector operates within an inherently dynamic and competitive environment, where firms face continuous pressures to enhance efficiency, reduce costs, and deliver value to increasingly discerning customers. These challenges have been significantly exacerbated by global disruptions such as the COVID-19 pandemic, which forced industries to reevaluate their operational resilience and strategic agility [1, 2].

The pandemic intensified competitive pressures while highlighting the critical importance of technological innovation in maintaining business continuity, addressing supply chain disruptions, and adapting to rapidly evolving market dynamics [6].

Competitive factors, including price, quality, and customization, drive technological adoption as firms strive to stay competitive and efficient in global markets [20]. These factors serve as catalysts for the development and integration of technologies that enhance production efficiency and organizational effectiveness, which is crucial for sustaining competitiveness in an era of heightened uncertainty and complexity [2, 7].

Production control systems optimize processes, reduce waste, and enhance efficiency, addressing competitive complexities and ensuring timely delivery, making them essential for operational excellence [8, 9].

One of the most transformative aspects of modern production control systems is their integration of real-time monitoring capabilities and automated decision-making technologies. These advancements provide manufacturers with unparalleled flexibility and agility, enabling them to dynamically adjust production schedules and optimize operations in response to fluctuating market conditions [6]. Such responsiveness is increasingly viewed as a competitive necessity, particularly in environments where customer expectations for quality, customization, and rapid delivery are continually rising.

The role of production control systems goes beyond operational efficiency, offering significant strategic advantages. These systems enable firms to align their production processes with broader competitive goals, including cost reduction, quality improvement, and enhanced market responsiveness. Leveraging real-time data and predictive analytics, these systems optimize resource allocation while supporting proactive decision-making, helping firms mitigate risks and seize emerging opportunities.

Moreover, the adoption of production control systems is often driven by external pressures, including the need to meet stringent customer requirements and adapt to rapidly evolving market dynamics. As global supply chains become more complex, the ability to integrate production control systems with digital supply chain platforms has emerged as a key differentiator. Firms that effectively implement these systems are better positioned to navigate disruptions, maintain continuity, and sustain competitive advantage in an increasingly volatile business landscape.

Building on these insights from the literature, we propose the Hypothesis 1.

H1: *Competitive factors positively influence the adoption of Production Control Systems* [8, 9]. This hypothesis reflects the critical role of competitive pressures in shaping the technological strategies of manufacturing firms, highlighting the strategic imperative for adopting production control systems in response to market demands and operational challenges.

The integration of automation and robotics into manufacturing processes represents a critical advancement for industries seeking to enhance productivity, reduce costs, and remain competitive in global markets. The increasing adoption of automation technologies, such as robotic arms, automated assembly lines, and AI-enabled systems, demonstrates their role in meeting the growing demands for faster, more consistent, and cost-efficient production [2]. These technologies enable firms to significantly improve production speed and reliability while minimizing labor costs—key factors in industries where efficiency and scalability are paramount [21].

Automation technologies ensure quality and consistency by minimizing human variability and meeting high customer expectations [2]. Furthermore, the scalability offered by these technologies allows firms to quickly adapt to fluctuating market demands, enabling faster production ramp-ups during periods of increased consumer activity.

The competitive pressures driving automation adoption extend beyond cost efficiency. In industries characterized by tight margins and high customer expectations, automation provides a strategic advantage by enabling firms to meet delivery deadlines and ensure consistent product quality. Automation also fosters innovation in manufacturing processes, allowing for the development of more flexible production systems that can accommodate diverse product configurations and customizations. As such, the role of automation extends beyond operational efficiency to encompass strategic imperatives for market competitiveness.

These considerations underline the critical relationship between competitive pressures and the adoption of automation technologies. Based on this analysis, we propose Hypothesis 2.

H2: *Competitive factors positively influence the adoption of Automation and Robotics* [2, 20]. This hypothesis highlights the role of automation as a transformative tool that enables firms to align their production processes with the demands of competitive global markets.

The adoption of efficiency technologies has similarly become a focal point for firms seeking to navigate the dual challenges of rising operational costs and increasing regulatory scrutiny. Efficiency technologies, which encompass innovations such as energy-efficient systems, advanced waste reduction mechanisms, and precision process controls, are pivotal for addressing these challenges while simultaneously improving sustainability and cost-effectiveness [7]. These technologies align with the global trend toward environmentally responsible manufacturing practices and play a crucial role for firms seeking to improve resource utilization and lower operational expenses.

The pressures to adopt efficiency technologies are particularly pronounced in industries where energy costs represent a significant portion of production expenditures. Innovations in energy recovery systems, smart grid integration, and waste recycling processes have enabled firms to reduce energy consumption and material waste, directly contributing to operational cost savings [12]. Furthermore, regulatory frameworks increasingly emphasize sustainability, compelling firms to adopt these technologies to ensure compliance with environmental standards while maintaining their market competitiveness.

Efficiency technologies also play a key role in aligning firms with broader societal demands for sustainability. Consumers and stakeholders increasingly expect organizations to operate in environmentally responsible ways, making the adoption of such technologies an important driver of corporate reputation and brand value. Beyond compliance, efficiency technologies provide firms with the tools to proactively address global challenges such as climate change and resource scarcity, positioning them as leaders in sustainability-driven innovation.

In light of these factors, the adoption of efficiency technologies is intrinsically linked to competitive pressures and strategic imperatives for sustainability. Firms that successfully integrate these technologies are better positioned to navigate market and regulatory challenges while simultaneously enhancing their operational efficiency. Building on these insights, we propose Hypothesis 3.

H3: *Competitive factors positively influence the adoption of Efficiency Technologies* [7, 12]. This hypothesis reflects the critical role of efficiency technologies in balancing cost-efficiency, compliance, and sustainability, further solidifying their importance in modern manufacturing landscapes.

The increasing demand for customized products has become a significant driver for adopting additive manufacturing (AM) and simulation tools across various industries. AM technologies, such as 3D printing, offer transformative capabilities by enabling firms to produce highly customized components with speed and cost-efficiency. By bypassing the need for expensive molds or retooling processes, these technologies provide unprecedented flexibility in meeting customer-specific requirements [7]. This adaptability is especially critical in competitive markets where responsiveness and differentiation are key to maintaining a competitive edge. Moreover, the ability of AM technologies to streamline production cycles aligns with the broader industry push for rapid innovation and shortened time-to-market [6].

Simulation tools complement AM technologies by enhancing production planning and decision-making. By allowing firms to test and evaluate various production scenarios before physical implementation, simulation tools reduce production risks and optimize resource allocation [6]. These tools enable manufacturers to anticipate challenges, minimize inefficiencies, and ensure smoother production workflows, which are crucial in industries with high customization demands. Together, AM and simulation tools represent an integrated approach to addressing the challenges of modern manufacturing, particularly in contexts where speed, customization, and efficiency are indispensable. Based on this analysis, we propose Hypothesis 4.

H4: *Competitive factors positively influence the adoption of Additive Manufacturing and Simulation Tools* [6, 7]. Beyond individual technological solutions, technological innovation capabilities (TICs) have been identified as essential enablers for the successful adoption and integration of advanced manufacturing technologies. TICs encompass a firm's capacity to leverage internal resources, such as learning capabilities and marketing strategies, to adapt to evolving market conditions and implement new technologies effectively [1]. These capabilities become particularly critical during periods of disruption, such as the COVID-19 pandemic, where agility and strategic foresight determine a firm's ability to sustain operations and capitalize on emerging opportunities. TICs play a pivotal role in enhancing the integration of automation, additive manufacturing, and other advanced technologies by aligning them with broader strategic goals. Firms that effectively harness TICs are better equipped to create innovation-driven production systems, enhancing operational efficiency and building competitive advantage through strategic planning and resource management [2]. These capabilities emphasize the role of competitive factors in driving technological adoption and further illustrate the interconnected nature of automation, additive manufacturing, and innovation capabilities [1, 6].

This theoretical review highlights the critical role of competitive factors in driving the adoption of advanced manufacturing technologies. Production control systems, automation and robotics, efficiency technologies, and additive manufacturing are all shown to be influenced by the pressures to improve cost-efficiency, quality, and customization in response to evolving market demands. Additionally, the importance of technological innovation capabilities is demonstrated as a key enabler for successfully integrating these technologies into organizational practices.

The proposed hypotheses—H1 through H4—reflect the complex interplay between competitive pressures, technological adoption, and organizational capabilities, providing a comprehensive framework for understanding the dynamics of modern manufacturing.

2.2 Technological advancements as drivers of organizational dynamics

The integration of advanced technologies, including production control systems, automation, and robotics, has fundamentally reshaped manufacturing operations, leading to significant changes in organizational structures and management practices. These technologies, influenced by competitive pressures and technological innovation, improve operational efficiency and strengthen the strategic capabilities of firms to adapt to dynamic market environments. This section examines the organizational implications of these advancements, focusing on their impact on production organization and management.

Production control systems are foundational to modern manufacturing, playing a critical role in optimizing resource allocation, minimizing waste, and enhancing overall operational efficiency. By providing real-time visibility into production processes, these systems enable firms to achieve higher levels of coordination and precision, ensuring that production activities align closely with organizational objectives [10]. The adoption of these systems also fosters a culture of continuous improvement, where inefficiencies are identified and addressed proactively, contributing to improved organizational performance [11].

Moreover, production control systems support the implementation of lean manufacturing principles, which prioritize waste reduction and process efficiency. These systems enable firms to streamline workflows, reduce production downtime, and optimize inventory management, thereby strengthening the organization of production. As firms adopt these technologies, they often experience a shift towards more integrated and agile production models, which are better suited to the demands of competitive markets.

The organizational benefits of production control systems include improved operational efficiency, enhanced employee engagement, and better work characteristics. Automating routine tasks and delivering actionable insights allow for a more strategic allocation of human resources, enabling personnel to concentrate on higher-value activities. This approach enhances productivity and fosters a more dynamic and adaptable organizational structure. Based on this analysis, we propose Hypothesis 5.

H5: *Production Control positively influences the Organization of Production* [10, 11]. In addition to their impact on the organization of production, production control systems play a crucial role in enhancing production management practices. These systems provide managers with detailed, real-time data on production performance, enabling more informed and timely decision-making. The ability to monitor production processes dynamically and identify inefficiencies allows managers to implement corrective measures swiftly, ensuring that production goals are met with minimal disruptions [17].

The integration of advanced production control systems also facilitates strategic resource management by providing tools for predictive analytics and scenario planning. These capabilities allow firms to anticipate potential bottlenecks, allocate resources more effectively, and maintain production schedules with greater accuracy. As a result, organizations leveraging these systems are better equipped to respond to fluctuating market demands and align their production strategies with broader business objectives [13].

Furthermore, production control systems enhance the responsiveness and agility of organizations, which are critical factors in today's fast-paced manufacturing landscape. By enabling firms to adjust production schedules in real-time and optimize operational workflows, these systems contribute to improved customer satisfaction and competitive positioning. Based on these insights, we propose Hypothesis 6.

H6: *Production Control positively influences Production Management/Controlling* [13, 17, 23]. Automation technologies have become a cornerstone of modern manufacturing, fundamentally reshaping production organization and management. These technologies enhance productivity and efficiency by automating repetitive tasks, standardizing processes, and reducing human error, all of which contribute to a more organized and reliable production environment [24]. By streamlining workflows and improving supply chain management, automation enables firms to achieve greater consistency and responsiveness in their operations. The standardization brought about by automated systems reduces variability, ensuring that production outputs meet quality standards while minimizing delays and inefficiencies [23].

Furthermore, automation technologies such as robotics have extended their impact beyond the shop floor to strategic production planning. Robotic systems, capable of performing intricate tasks with precision and speed, have enabled firms to scale production without proportionate increases in labor costs. These systems also facilitate rapid adjustments to production schedules, accommodating changes in demand with minimal disruption. Given these advancements, we propose Hypothesis 7.

H7: *Automation and Robotics positively influence the Organization of Production* [23, 24]. Automation also plays a critical role in improving management practices. By integrating advanced monitoring and control systems, automation provides managers with real-time insights into production performance, equipment status, and resource utilization. This enhanced visibility enables managers to make more informed decisions, implement corrective actions promptly, and optimize production schedules to align with organizational goals [13]. Automation technologies further improve scalability by allowing firms to expand operations seamlessly, supporting higher production volumes without compromising efficiency or quality [25].

The ability to automate complex decision-making processes also contributes to the development of more agile and adaptable production management systems. Predictive analytics and machine learning algorithms embedded within automated systems offer managers the tools to anticipate production challenges, optimize resource allocation, and streamline workflows. Consequently, we propose Hypothesis 8.

H8: *Automation and Robotics positively influence Production Management/Controlling* [13, 25]. Efficiency technologies, encompassing innovations such as energy recovery systems, automated guided vehicles (AGVs), and advanced process controls, have become vital for fostering sustainable and resource-efficient production frameworks. These technologies optimize material flows, reduce resource wastage, and enhance the overall sustainability of manufacturing operations [15]. By integrating energy-efficient systems and waste reduction mechanisms, firms can achieve significant cost savings while simultaneously aligning with global sustainability goals. Such advancements contribute to more organized production environments by promoting resource efficiency and minimizing environmental impact [26].

Efficiency technologies enable firms to meet stringent regulatory requirements and address stakeholder expectations effectively. Adopting these technologies improves operational performance while enhancing corporate reputation by showcasing a commitment to sustainability. Given these considerations, we propose Hypothesis 9.

H9: *Efficiency Technologies positively influence the Organization of Production* [26]. Beyond their impact on production organization, efficiency technologies also enhance production management practices by enabling real-time monitoring and control. For instance, energy recovery systems and water recycling technologies provide managers with detailed insights into resource consumption and waste patterns. These insights facilitate evidence-based decision-making and enable organizations to implement targeted interventions that improve efficiency and reduce costs [27]. Additionally, real-time data visualization capabilities allow managers to identify inefficiencies, optimize production processes, and achieve continuous improvement [28]. Based on these observations, we propose Hypothesis 10.

H10: *Efficiency Technologies positively influence Production Management/Controlling* [27, 28]. Additive manufacturing (AM) and simulation tools represent transformative technologies that have redefined the way firms approach production organization and management. These technologies streamline workflows by minimizing inefficiencies and fostering operational agility, which is critical in dynamic and highly competitive manufacturing environments. Additive manufacturing, such as 3D printing, enables firms to adopt flexible production setups, facilitating the rapid production of customized parts without the need for expensive molds or extensive retooling [29]. This adaptability is particularly valuable for meeting customer-specific demands while maintaining cost-effectiveness and efficiency.

Simulation tools complement AM by providing the capability to optimize production processes before physical implementation. By enabling the modeling of various production scenarios, simulation tools allow firms to identify potential bottlenecks, test different configurations, and choose the most efficient and effective production strategies [23]. This integration of AM and simulation tools enhances organizational agility and supports a more streamlined production system. Based on these observations, we propose Hypothesis 11.

H11: *Additive Manufacturing and Simulation Tools positively influence the Organization of Production* [29, 30]. In addition to their impact on production organization, AM and simulation tools contribute significantly to advancing production management practices. The real-time visualization capabilities of AM technologies enable firms to monitor production processes with precision, facilitating proactive adjustments and reducing the likelihood of production errors. These tools enhance predictive quality assurance, allowing firms to detect inefficiencies early in the production cycle and implement corrective actions to maintain consistency and reliability [31].

Simulation tools further support production management by offering detailed insights into process dynamics and potential outcomes. These tools enable managers to evaluate alternative strategies, optimize resource allocation, and plan for contingencies, thereby improving the overall effectiveness of production management systems [32]. Together, AM and simulation tools foster a data-driven approach to production management that emphasizes precision, adaptability, and continuous improvement. Accordingly, we propose Hypothesis 12.

H12: *Additive Manufacturing and Simulation Tools positively influence Production Management/Controlling* [31, 32]. The successful integration of additive manufacturing, simulation tools, and other advanced technologies is contingent on their alignment with complementary organizational practices. Isolated implementations of these technologies may yield incremental improvements, but their full potential is realized only when integrated into a cohesive strategy that incorporates organizational design, workforce capabilities, and process optimization. This synergistic approach fosters enhanced operational performance and sustainable competitive advantage [33, 34].

The alignment of technological advancements with organizational strategies also facilitates innovation by enabling firms to respond more effectively to changing market conditions. By leveraging the strengths of both technology and organizational practices, firms can optimize their production systems, improve decision-making, and achieve greater operational efficiency. This integrated approach higlights the importance of considering both technological and organizational dimensions when implementing advanced manufacturing solutions.

The theoretical review highlights the transformative potential of advanced manufacturing technologies—including production control systems, automation, robotics, efficiency technologies, additive manufacturing, and simulation tools—in reshaping organizational dynamics. These technologies enhance production organization and management by improving operational efficiency, enabling agility, and fostering sustainability.

The proposed hypotheses (H5 through H12) provide a comprehensive framework for understanding the interplay between technological advancements and organizational strategies, offering a roadmap for empirical investigations. By integrating these technologies with complementary organizational practices, firms can achieve sustainable operational performance and maintain a competitive edge in an increasingly complex and dynamic manufacturing landscape.

The hypotheses formulated in this study summarize the proposed relationships between competitive factors, technological advancements, and their impact on organizational dynamics. These relationships are systematically outlined and presented in Table 1, providing a structured framework for further empirical validation and analysis.

Table 1 Research hypothesis

Hypothesis 1 (H1): *Competitive factors positively influence Production Control.*
Hypothesis 2 (H2): *Competitive factors positively influence Automation and Robotics.*
Hypothesis 3 (H3): *Competitive factors positively influence Efficiency Technologies.*
Hypothesis 4 (H4): *Competitive factors positively influence Additive Technologies/Simulation Tools.*
Hypothesis 5 (H5): *Production Control positively influences Organization of Production.*
Hypothesis 6 (H6): *Production Control positively influences Production Management/Controlling.*
Hypothesis 7 (H7): *Automation and Robotics positively influence Organization of Production.*
Hypothesis 8 (H8): *Automation and Robotics positively influence Production Management/Controlling.*
Hypothesis 9 (H9): *Efficiency Technologies positively influence Organization of Production.*
Hypothesis 10 (H10): *Efficiency Technologies positively influence Production Management/Controlling.*
Hypothesis 11 (H11): *Additive Technologies/Simulation Tools positively influence Organization of Production.*
Hypothesis 12 (H12): *Additive Technologies/Simulation Tools positively influence Production Management/Controlling.*

3. Materials and methods

3.1 Data and sample

The data utilized in this study were collected in 2022 as part of the European Manufacturing Survey (EMS), coordinated by the Fraunhofer Institute for Systems and Innovation Research. The survey targeted manufacturing firms operating within the Republic of Serbia with a workforce of more than 20 employees. Respondents included key decision-makers such as CEOs, production managers, and other employees holding roles relevant to production practices. Data collection employed a closed-type questionnaire, in which participants indicated the implementation of specific production practices by selecting binary options (1 for implementation, 0 for non-implementation). The Dillman method was applied to ensure effective participant engagement, achieving a response rate of 31.95 %.

The sample consisted of 146 manufacturing firms, selected using the Cochran formula and stratified based on firm size, industrial sector, and geographic location within Serbia. The stratified sampling approach ensured a representative cross-section of Serbia's manufacturing landscape. Firms were classified into three size categories: small (20-49 employees), medium (50-249 employees), and large (250 or more employees). Small firms constituted 45 % of the sample (65 firms), medium-sized firms accounted for 39 % (57 firms), and large firms comprised the remaining 16 % (24 firms).

Sectoral classification adhered to the NACE framework, reflecting the diversity of industrial activities. The manufacture of fabricated metal products, excluding machinery and equipment (NACE 25), represented the largest segment, accounting for 19 % of the sample (28 firms). This was followed by the manufacture of food products (NACE 10), comprising 16 % of the sample (24 firms). Other notable sectors included the manufacture of rubber and plastic products (NACE 22) with 8 % (12 firms), wearing apparel (NACE 14) and machinery and equipment n.e.c. (NACE 28) each at 6 % (9 firms per sector), and non-metallic mineral products (NACE 23) and basic metals (NACE 24), each contributing 5 % (8 firms per sector). The remaining 35 % of the sample (48 firms) encompassed a variety of other industrial sectors, providing a comprehensive representation of manufacturing activities within the country.

This stratified sampling approach ensured that the data reflected the structural and operational characteristics of Serbia's manufacturing sector across diverse firm sizes and industrial categories. The representativeness of the sample enhances the generalizability of the study's findings, providing robust insights into production practices within the regional manufacturing context.

3.2 Testing of the research model

The research model was established based on the theoretical framework provided by the European Manufacturing Survey (EMS), as developed and structured by Fraunhofer-ISI, Germany. The predefined factorial structure of the EMS served as the foundation for categorizing organizational and technological concepts relevant to this study. Organizational concepts were defined as comprising (1) "Organization of the Production" and (2) "Production Management and Controlling," while technological concepts were categorized into (1) "Production Control (Digital Factory)," (2) "Automation and Robotics," (3) "Efficiency Technologies," and (4) "Additive Technologies and Simulation Tools." The manifest variables associated with these factors, along with their respective items, are detailed in Table 2.

Table 2 A predefined factor structure of the research instrument

Encoded	Factors	Items
U1	Organization of the production	Integration of tasks
U2		Customer- or product-oriented lines/cells in the factory
U3		Production controlling following the Pull principle
U4		Methods for optimizing change-over time or reducing setup time
U5		Standardized and detailed work instructions
U6	Production management/controlling	Visual management and monitoring of work processes and work status on display boards in production
U7		Methods of assuring quality in production
U8		Employee involvement in innovation development
U9		Employee bonus systems for outstanding performances in production and/or innovation
U10		Certified environmental management system
U11	Production control	Mobile/wireless devices for programming and controlling machinery and/or facilities
U12		Digital solutions to provide drawings, work schedules, or work instructions directly on the shop floor
U13		Software for production planning and scheduling
U14		Techniques for automation and management of internal logistics
U15		Digital Exchange of product/process data with suppliers/customers
U16		Product-Lifecycle-Management-Systems (PLM) or Product/Process Data Management
U17		Near real-time production control system
U18	Automation and robots	Industrial robots for manufacturing processes
U19		Industrial robots for handling processes
U20	Efficiency technologies	Technologies to recuperate kinetic and process energy
U21		Technologies for recycling and re-use of water
U22	Additive technologies and simulation tools	3D printing technologies for prototyping
U23		Software for product design simulation
U24		Software for simulating production processes
U25	Competitive factors	Product price
U26		Product quality
U27		Customizations to customers' demand

The research model was developed through a two-step approach [19]. In the first step, the validity of the measurement model was assessed using Confirmatory Factor Analysis (CFA). This method was employed to evaluate the adequacy of the factor structure and to confirm the hypothesized relationships among latent constructs. In the second step, Structural Equation Modeling (SEM) was applied to analyze the interrelationships between the identified factors, ensuring a robust examination of the theoretical framework [18, 19].

Given that the questionnaire was designed with a three-point item scale (e.g., low, medium, high), traditional reliability measures, such as the Cronbach alpha coefficient, were not applicable [35]. Instead, the Weighted Least Square Mean and Variance adjusted (WLSMV) estimation method was utilized for extracting the factor structure. This method, recognized for its robustness in handling ordinal data, was implemented using the *Mplus* statistical software [18]. The WLSMV approach ensured that the analysis accounted for the categorical nature of the data while maintaining statistical rigor.

3.3 Testing the measurement model – CFA

The validity of the measurement model was assessed using Confirmatory Factor Analysis (CFA), which confirmed the appropriateness of the predefined factorial structure. All factor loadings were found to be statistically significant, with t-values exceeding the critical threshold of 1.96, indicating robust convergent validity [18, 19]. Standardized factor loadings, along with their associated standard errors, t-values, and p-values, are summarized in Table 3.

The results demonstrate the strength of the associations between latent constructs and their respective manifest variables, supporting the theoretical assumptions underlying the model.

Furthermore, the CFA results revealed that the measurement model exhibited excellent fit indices, ensuring the suitability of the model for subsequent Structural Equation Modeling (SEM) analysis. These findings demonstrate the robustness of the research instrument and its consistency with the theoretical framework. The empirically tested model is illustrated in Fig. 1.

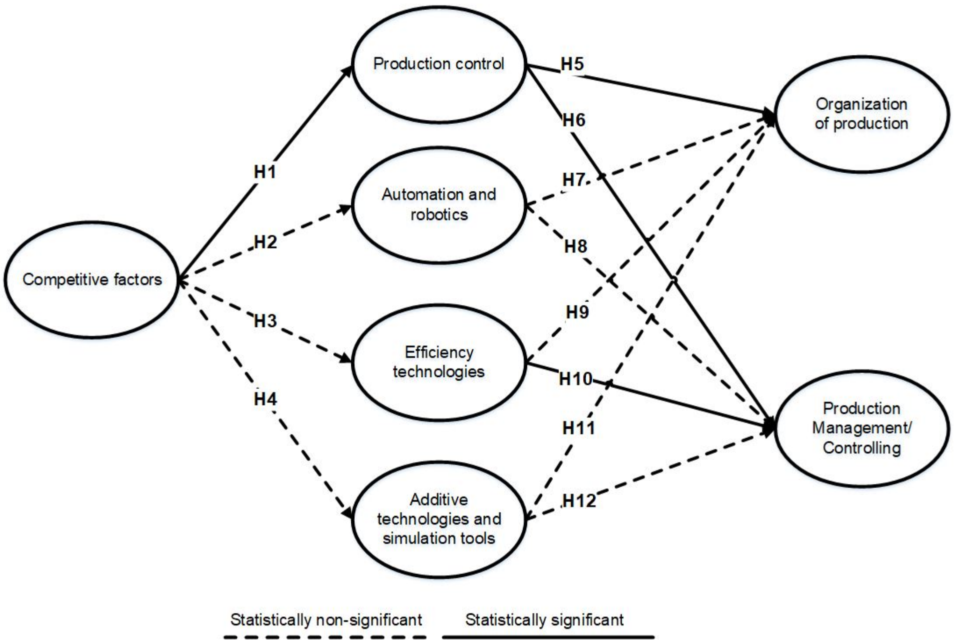

Fig. 1 Empirically tested model

Table 3 Convergent validity model results (CFA)

Encoded	Factors	λ	e	t	p	Sig.
U1	Organization of production	0.544	0.076	7.163	0.000	Yes
U2		0.705	0.065	10.860	0.000	Yes
U3		0.622	0.080	7.813	0.000	Yes
U4		0.850	0.052	16.433	0.000	Yes
U5		0.787	0.062	12.762	0.000	Yes
U6	Production management/controlling	0.698	0.066	10.519	0.000	Yes
U7		0.768	0.051	14.927	0.000	Yes
U8		0.731	0.068	10.808	0.000	Yes
U9		0.560	0.072	7.780	0.000	Yes
U10		0.666	0.069	9.590	0.000	Yes

Table 3 (Continuation)

U11	Production control	0.652	0.085	7.628	0.000	Yes
U12		0.617	0.079	7.833	0.000	Yes
U13		0.755	0.065	11.630	0.000	Yes
U14		0.744	0.061	12.191	0.000	Yes
U15		0.715	0.063	11.363	0.000	Yes
U16		0.798	0.065	12.251	0.000	Yes
U17		0.715	0.072	9.993	0.000	Yes
U18	Automation and robots	0.812	0.122	6.647	0.000	Yes
U19		0.807	0.116	6.982	0.000	Yes
U20	Efficiency technologies	0.639	0.133	4.810	0.000	Yes
U21		0.816	0.141	5.790	0.000	Yes
U22	Additive technologies and Simulation tools	0.813	0.099	8.213	0.000	Yes
U23		0.761	0.078	9.778	0.000	Yes
U24		0.931	0.119	7.811	0.000	Yes
U25	Competitive factors	0.577	0.118	4.899	0.000	Yes
U26		0.461	0.103	4.456	0.000	Yes
U27		0.284	0.078	3.650	0.000	Yes

3.4 Structural model testing – SEM

Structural Equation Modeling (SEM) was conducted to evaluate the interrelationships between the latent constructs identified through the CFA. The SEM analysis confirmed that all fit indices were within the recommended thresholds, demonstrating the overall adequacy of the model fit [18, 19]. A summary of the goodness-of-fit statistics is presented in Table 4.

The model exhibited strong fit indices, including a chi-square statistic to degrees of freedom ratio (χ^2/df) of 1.248, which falls well within the acceptable range of ≤ 2.0-3.0. The Root-Mean-Square Error of Approximation (RMSEA) was 0.041, below the recommended maximum of 0.08, indicating a close fit of the model to the data. Additionally, the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) values of 0.925 and 0.915, respectively, were above the minimum recommended threshold of 0.90, further confirming the robustness of the model.

These findings provide empirical support for the theoretical assumptions underpinning the study and validate the proposed relationships between organizational and technological constructs. The SEM analysis effectively integrates the theoretical framework with empirical data, offering a comprehensive understanding of the dynamics at play within the manufacturing sector.

Table 4 Goodness-of-fit statistics

Model	Baseline model χ^2	χ^2	df	χ^2/df	RMSEA	CFI	TLI
CFA	1381.178	382.064*	303	1.261	0.042	0.923	0.911
SEM		388.245*	311	1.248	0.041	0.925	0.915
Rec. values	Comparison	Less the better	-	≤ 2, 3	< 0.08	> 0.95	> 0.90

*p – Statistical significance, value < 0.01; df – Degrees of freedom, $\chi 2$ – Chi-square statistic, RMSEA – Root-mean-square error of approximation; CFI – Comparative fit index; TLI – Tucker-Lewis index

4. Results and discussion

4.1 Analysis of mutual influences of researched concepts

The results of the Structural Equation Modeling (SEM) provide a comprehensive understanding of the relationships between competitive factors, technological adoption, and their influence on organizational practices. The SEM framework reveals the statistically significant impact of competitive factors on Production Control Systems, while other advanced technologies, such as Automation and Robotics, Efficiency Technologies, and Additive Technologies and Simulation Tools, show no significant effects. These findings reveal the intricate relationship between external pressures and technological integration in manufacturing settings.

As illustrated in Table 5, competitive factors exhibit a strong and statistically significant positive influence on the adoption of Production Control Systems (Γ = 0.384, t = 3.267, p = 0.001). This highlights the strategic imperative for manufacturing firms to implement production control systems as a response to external pressures, including product customization, quality assurance, and competitive pricing. These findings align with prior studies suggesting that firms often prioritize technologies offering immediate operational benefits under competitive stress [8].

However, competitive factors did not demonstrate significant effects on Automation and Robotics ($\Gamma = 0.211$, $t = 1.528$, $p = 0.126$), Efficiency Technologies ($\Gamma = 0.179$, $t = 1.105$, $p = 0.269$), or Additive Technologies and Simulation Tools ($\Gamma = 0.102$, $t = 0.586$, $p = 0.558$). This discrepancy suggests that while production control systems are perceived as essential for maintaining competitive advantage, the adoption of other advanced technologies may depend on firm-specific variables such as financial capacity, technological readiness, or workforce skills.

Table 5 summarizes these findings.

Table 5 The influence of competitive factors on technological concepts

	→ Technologies	*Γ*	*e*	***t***	***p***	*Sig.*
Competitive Factors →	Production control	0.384	0.117	3.267	0.001*	Yes
	Automation and robotics	0.211	0.138	1.528	0.126	No
	Efficiency technologies	0.179	0.162	1.105	0.269	No
	Additive technologies and simulation tools	0.102	0.174	0.586	0.558	No

Γ – Gamma value of the coefficient between the independent (competitive factors) and dependent (technological concepts) variable; e – Standard error, t–t statistics (statistically significant at value $t \geq 1.96$), p – statistical significance, * – Statistically significant relationship at value $p \leq 0.01$

The study further explored the influence of technologies on two critical organizational constructs: Organization of Production and Production Management/Controlling. As shown in Table 6, Production Control Systems positively and significantly impact both constructs: Organization of Production ($\beta = 0.384$, $t = 3.267$, $p = 0.001$) and Production Management/Controlling ($\beta = 0.500$, $t = 4.010$, $p = 0.000$). This supports the hypothesis that production control systems act as a central enabler of both operational efficiency and strategic decision-making [10].

Interestingly, Efficiency Technologies demonstrated a significant positive effect on Production Management/Controlling ($\beta = 0.381$, $t = 2.604$, $p = 0.009$), reflecting their critical role in aligning operations with sustainability goals. However, they did not significantly impact Organization of Production ($\beta = 0.179$, $t = 1.105$, $p = 0.269$), indicating that their benefits may be limited to operational refinements rather than structural transformations.

Automation, robotics, additive technologies, and simulation tools showed no statistically significant impact on either organizational construct, as reflected in Table 6. This result suggests that these technologies may require greater contextual integration or complementary organizational practices to deliver measurable benefits. Although managerial culture was not directly measured in this research, the observed path structure offers a context-specific reading for Serbia. Competitive factors significantly increase the adoption of Production Control Systems ($\Gamma = 0.384$; $p = 0.001$), and Production Control Systems in turn exhibit strong positive effects on both Organization of Production and Production Management/Controlling ($\beta = 0.384$; $p = 0.001$; $\beta = 0.500$; $p < 0.001$). Because the Production Control Systems construct (U11-U17) emphasises real-time monitoring, planning/scheduling and digital work instructions, while OP/PMC (U1-U10) capture standardized work, visual management, quality assurance and certified environmental management, this pattern is consistent with managerial preferences for control oriented, auditable improvements.

Conversely, Automation/Robotics and Additive/Simulation show no significant effects in our model (Tables 5-6), indicating that more capability-intensive or disruptive technologies may face higher organisational thresholds (skills, routines, change management) before yielding measurable organisational impacts. The Efficiency Technologies → Production Control Systems path ($\beta = 0.381$; $p = 0.009$) further suggests a compliance- and monitoring-driven orientation of management systems, where energy/waste initiatives are integrated into formal controlling rather than reconfiguring the organisation of production.

A consolidated summary of the hypothesized relationships and their statistical significance is presented in Table 7.

Table 6 The influence of technology on organizational concepts

Technologies→	Organizational concepts	*β*	*e*	*t*	*p*	Sig.
Production control	Organization of production	0.384	0.117	3.267	0.001*	Yes
	Production management/controlling	0.500	0.125	4.010	0.000*	Yes
Automation and Robotics	Organization of production	0.211	0.138	1.528	0.126	No
	Production management/controlling	0.136	0.185	0.734	0.463	No
Efficiency technologies	Organization of production	0.179	0.162	1.105	0.269	No
	Production management/controlling	0.381	0.146	2.604	0.009*	Yes
Additive technologies and simulation tools	Organization of production	0.102	0.174	0.586	0.558	No
	Production management/controlling	0.158	0.172	0.920	0.358	No

β – Beta value of the coefficient between the dependent (technological concepts) and the dependent (organizational concepts) variable*; e* – Standard error, *t–t* statistics (statistically significant at value $t \geq 1.96$), *p – statistical significance,* * – Statistically significant relationship at value $p \leq 0.01$

Table 7 A summary of the tested hypotheses of mutual influence

Encoded	From →	→ To	Sig.
H1	Competitive Factors	Production control	Yes
H2		Automation and Robotics	No
H3		Efficiency technologies	No
H4		Additive technologies and Simulation tools	No
H5	Production control	Organization of production	Yes
H6		Production management/controlling	Yes
H7	Automation and robotics	Organization of production	No
H8		Production management/controlling	No
H9	Efficiency technologies	Organization of production	No
H10		Production management/controlling	Yes
H11	Additive technologies and simulation tools	Organization of production	No
H12		Production management/controlling	No

Sig. – Semantic marking of statistical significance

4.2 Theoretical and practical implications

This study contributes to the growing body of literature exploring the interplay between competitive pressures and technological adoption. By confirming the statistically significant influence of competitive factors on Production Control Systems, it builds on existing frameworks emphasizing the strategic importance of technologies that enable agility and operational efficiency in highly dynamic markets [6, 8]. The lack of significant relationships for other advanced technologies—such as Automation and Robotics, Efficiency Technologies, and Additive Manufacturing and Simulation Tools—challenges the assumption of uniform adoption patterns and highlights the selective prioritization of technologies based on immediate operational needs and resource availability.

The findings also expand the understanding of how technological advancements influence organizational constructs. Production Control Systems emerge as central to both Organization of Production and Production Management/Controlling, reinforcing their role as a critical enabler of real-time decision-making and process optimization. The statistically significant influence of Efficiency Technologies on Production Management/Controlling further higlights the alignment of these technologies with sustainability-driven operational strategies, contributing to broader discussions on the integration of environmental responsibility in manufacturing practices [12]. Beyond immediate efficiency gains, Production Control Systems contribute to long-term sustainability outcomes by minimizing waste, ensuring traceability across the supply chain, and supporting compliance with environmental standards. These systems therefore act as dual enablers of operational excellence and sustainable manufacturing.

For practitioners, these results offer actionable insights into prioritizing technological investments under competitive pressures. Firms aiming to enhance their operational and strategic capabilities should prioritize the adoption of Production Control Systems, which consistently deliver measurable improvements in process integration and decision-making. These systems address immediate competitive challenges and establish a foundation for broader technological integration, fostering resilience and adaptability in increasingly volatile markets.

The limited impact of other technologies highlights the importance of addressing barriers to adoption, such as high implementation costs, technical complexity, and resistance to organizational change. Overcoming these barriers requires a multi-layered approach that combines workforce, managerial, and systemic interventions.

At the workforce level, firms should establish structured digital upskilling programs aligned with Industry 4.0 competence frameworks, focusing on robotics operation, data analytics, simulation modeling, and energy-efficiency practices. Micro-credentialing schemes, recognized across sectors, could accelerate employee adaptation while ensuring standardization of new skills.

At the managerial level, executive development programs tailored to digital manufacturing should be introduced, emphasizing strategic technology roadmapping, change management, and sustainability-oriented decision-making. Such programs should integrate scenario-based training and digital twin simulations, enabling managers to anticipate operational bottlenecks and evaluate technology investment trade-offs in risk-controlled environments.

At the organizational level, establishing innovation hubs and testbeds within industrial clusters would allow firms to pilot automation, additive manufacturing, and efficiency technologies in shared, lower-risk environments. These collaborative platforms could foster joint experimentation, peer-to-peer learning, and cross-sectoral knowledge transfer.

At the policy level, supportive frameworks are essential. These may include targeted financial instruments (e.g., technology adoption tax credits, subsidized loans, or green transition vouchers), regulatory sandboxes to reduce compliance uncertainty, and public–private partnerships that co-invest in demonstrator projects. National-level initiatives could further incentivize adoption by linking technology integration to sustainability certification and international competitiveness benchmarks.

Collectively, these programs enhance absorptive capacity, reduce resistance to change, and create pathways for more seamless integration of advanced technologies into organizational practices.

4.3 Limitations and future directions

This study offers valuable insights but is not without limitations. This study is based on a cross-sectional design, which restricts the ability to establish causal relationships between competitive factors, technological adoption, and organizational outcomes. Longitudinal research designs would allow for capturing the temporal dynamics of these relationships, offering deeper insights into how technological integration evolves over time.

The analysis focuses exclusively on the Serbian manufacturing sector. While this provides valuable regional insights, it also limits the generalizability of the findings. Extending the empirical validation of the proposed model to other contexts—particularly Western Europe and Asia, where institutional support and technological maturity are higher—could reveal different adoption patterns and organizational outcomes.

The EMS dataset used in this study did not include emerging technologies such as Artificial Intelligence (AI) and Large Language Models (LLMs). These technologies may represent transformative forces that could rival or even surpass the effects of automation and simulation tools. Future studies should examine how such technologies interact with competitive pressures and reshape organizational practices, especially in digitally transforming and knowledge-intensive environments.

Although the sample was stratified by firm size, the analysis did not test whether financial constraints or organizational barriers vary systematically across small, medium, and large firms. Multi-group SEM or comparative approaches would provide more nuanced insights into how firm size moderates the role of resources and readiness in technology adoption. Moreover, organizational culture, leadership commitment, and innovation capabilities were not explicitly modeled, despite their likely critical influence on adoption success. Including these mediating and moderating factors in future research would provide a more holistic understanding of organizational transformation.

The study's scope could be expanded to include mediating and moderating factors that influence technological adoption and impact. For instance, organizational culture, leadership commitment, and innovation capabilities are likely to play critical roles in shaping the success of technological integration. Incorporating these factors into future models would provide a more holistic understanding of the mechanisms driving manufacturing excellence.

The results of this study inspire several avenues for future research. Key questions include:

- How do workforce skills and organizational learning capacities mediate the relationship between technology adoption and organizational outcomes?
- What synergies exist between different advanced technologies, and how can firms leverage these to maximize organizational benefits?
- What types of policy interventions are most effective in promoting the adoption of technologies with low immediate returns, such as Automation and Simulation Tools?

5. Conclusion

This study provides a scientifically rigorous examination of the interplay between competitive factors, technological adoption, and organizational dynamics in the Serbian manufacturing sector. Using data from the European Manufacturing Survey (EMS) and Structural Equation Modeling (SEM), it provides empirically validated insights into how firms prioritize technological investments and align them with competitive pressures and operational goals.

The findings underscore the importance of Production Control Systems as key to operational excellence, significantly influencing both the Organization of Production and Production Management/Controlling. These systems enable real-time process optimization, strategic decision-making, and agile responses to market fluctuations. While validating established production management theories, the study highlights selective technological adoption driven by factors such as financial capacity, workforce readiness, and regulatory frameworks. Technologies like Automation, Efficiency Technologies, and Additive Manufacturing are less uniformly adopted, reflecting these contextual constraints.

From a theoretical perspective, the research addresses gaps by providing a nuanced view of how competitive pressures shape technological strategies, challenging the notion of uniform adoption patterns. Production Control Systems emerge as critical enablers of operational and strategic benefits, with barriers to broader technology adoption identified.

Practically, the study offers actionable insights. Firms should prioritize technologies delivering immediate operational gains, such as Production Control Systems, while addressing adoption barriers for advanced solutions. Policymakers are advised to introduce targeted interventions—subsidies, training programs, and innovation hubs—to enhance firms' capacity for adopting transformative technologies.

In conclusion, the research advances both theoretical and practical understanding by demonstrating the pivotal role of competitive factors in technological adoption and organizational outcomes. By establishing Production Control Systems as central to manufacturing strategies, it lays the foundation for future studies aimed at fostering sustainable and innovation-driven operational frameworks in competitive markets.

Acknowledgement

This research has been supported by the Ministry of Science, Technological Development and Innovation (Contract No. 451-03-65/2024-03/200156) and the Faculty of Technical Sciences, University of Novi Sad through project "Scientific and Artistic Research Work of Researchers in Teaching and Associate Positions at the Faculty of Technical Sciences, University of Novi Sad" (No. 01-3394/1).

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