Precision Mechanics & Digital Fabrication
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Digital Transformation in Manufacturing: Enhancing Competitiveness Through Industry 4.0 Technologies

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Received: 02-05-2024 **Revised:** 03-18-2024 **Accepted:** 03-24-2024

Citation: I. M. Milošević, O. Plotnic, A. Tick, Z. Stanković, and A. Buzdugan, "Digital transformation in manufacturing: Enhancing competitiveness through Industry 4.0 technologies," *Precis. Mech. Digit. Fabr.*, vol. 1, no. 1, pp. 31–40, 2024. https://doi.org/10.56578/pmdf010104.

Abstract: The digitization of production processes in the manufacturing sector represents a pivotal transformation that fundamentally reshapes how companies achieve productivity, make informed decisions, and secure a competitive advantage. This research investigates the integration of Industry 4.0 technologies—including the Internet of Things (IoT), big data analytics, 3D printing, robotics, and artificial intelligence (AI)—within traditional manufacturing systems. The study focuses on three key dimensions driving digital transformation in manufacturing firms and examines their impact on digital platforms, which are increasingly critical for maintaining competitiveness in the digital age. The adoption of these platforms facilitates the seamless integration of Industry 4.0 technologies, thereby enhancing the growth potential and innovative capacity of manufacturing companies. This investigation involves a comprehensive analysis of data collected from 635 valid surveys across six countries—Serbia, Hungary, Poland, Slovakia, the Czech Republic, and Bulgaria—using Structural Equation Modeling (SEM). The findings confirm the significant influence of positive employee attitudes toward digitization and the intention to utilize digital tools on the successful adoption of Industry 4.0 technologies. These results underscore the necessity of fostering a culture that supports digital transformation, which, in turn, improves the efficiency and competitiveness of manufacturing firms. This study provides valuable insights into the future trajectory of digitization in the manufacturing sector, highlighting the essential role of digital platforms in the ongoing evolution of the industry.

Keywords: Digital transformation; Manufacturing sector; Industry 4.0 technologies; Production processes; Competitive advantage; Structural Equation Modeling

1 Introduction

The manufacturing industry has seen an important transition in recent times due to increasing global competition and the requirement for more adaptability [1]. Companies are implementing new strategies and technologies to improve their manufacturing processes in order to exist. This transformation is necessary for achieving improved connectedness and harmonization throughout all business processes and systems at all hierarchical levels of the organization and among all participants in the value chain [2]. As a result, Industry 4.0 technologies which include the IoT, big data analytics, 3D printing, robotics, advanced supply chain management, vertical integration, AI, 5G network, and virtual reality, have caused a paradigm shift that has greatly advanced manufacturing companies [3, 4]. This new technology wave initiated the development of digitization, automation, and data sharing in manufacturing [5]. According to the study conducted by Silvestri et al. [6], the digitalization of industrial processes prompts a transformation of conventional operating methods toward a more intelligent and interconnected framework. This indicates a fundamental transformation within the manufacturing industry. Managers and operators of manufacturing companies face numerous challenges brought about by the digital transition of manufacturing processes and systems [7]. Automation and digitization in production allow managers to improve decision-making to achieve a competitive advantage in an increasingly digital marketplace and operators to optimize their operations [8].

Integrating Industry 4.0 technologies into manufacturing systems requires adopting business models that heavily rely on digital platforms to utilize specialized, innovative digital tools and technologies as a means to achieve a competitive advantage [9, 10]. Digital platforms have appeared as tools for companies striving to maintain competitiveness in the digital era [9, 11]. By allowing for easy integration and application of Industry 4.0 technologies, digital platforms intensify manufacturing companies' innovation and growth potential [12].

Despite the numerous studies dealing with the digitization of production processes and the implementation of Industry 4.0 technologies, there is a literature gap regarding operators' attitudes and intentions regarding using digital platforms to facilitate the integration and operationalization of advanced technologies in manufacturing companies. Also, the existing research focused on analyzing highly industrialized countries, leaving a gap regarding the experiences and challenges companies face in developing economies.

Therefore, this paper aims to examine the crucial dimensions that drive manufacturing companies towards accepting digital platforms as a prerequisite for integrating and applying Industry 4.0 technologies. The dimensions that are analyzed are the attitudes, behavioral intentions, and intentions to use digitization by employees of manufacturing companies. For this purpose, four hypotheses were developed based on a deep literature review, which indicate that behavioral intention positively influences the use of digital platforms. Then, the second hypothesis is that the intention to use digital platforms positively affects their adoption. The third hypothesis points to the attitude towards digitization positively influencing the use of digital platforms. The last hypothesis deals with the acceptance of digital platforms positively affecting the adoption of Industry 4.0 technologies. Additionally, the research's focus spans six different countries, including Serbia, Hungary, Poland, Slovakia, the Czech Republic, and Bulgaria, providing a comprehensive view of the level of digitization in developing nations in manufacturing companies.

The study is structured as follows: an introduction is the first section, and then there is a literature review. The methodology is covered in detail in the third section, and the data analysis and results are shown in the fourth. A discussion of the findings comes next, and a conclusion is given in the last section.

2 Literature Review

Over time, industries have faced numerous challenges stemming from both internal and external environments [13]. Companies had to adopt sophisticated digital strategies, necessitating a dramatic change in production systems and manufacturing procedures [14]. Developing economies are particularly affected by the adoption of Industry 4.0 technologies, which significantly affect sustainability at the level of processes, systems, and products. These economies are increasingly focusing on the application of new technologies due to increased investments by multinational corporations, which encourages their integration into global flows [15]. One of the most revolutionary changes in the manufacturing sector, Industry 4.0, solved these issues by pointing to the real-time value-added digitization of production systems and manufacturing processes. Industry 4.0 has made several cutting-edge technological solutions available that can greatly increase productivity and empower workers to act quickly [13, 16]. According to Zhong et al.'s study [17], it can be defined as the digital transformation of industrial sectors that incorporate smart manufacturing. Urban et al. [18] suggested that the technologies of Industry 4.0 should be highlighted as pivotal to the emerging production era known as smart factories or smart manufacturing. According to Kusiak's study [19], smart manufacturing entails incorporating digital technologies into every facet of an organization's procedures and methods. Organizations can achieve advanced communication between machines and operators through the digitization of manufacturing systems and processes, resulting in increased productivity and a more efficient production environment [20].

Despite the vast potential and benefits of Industry 4.0 technologies, the literature highlights many issues with their adoption [21]. In the study conducted by Sinha and Kumar [22], it indicates the issues that prevent the manufacturing sector from applying Industry 4.0 and the consequences that will be faced in the future. Implementing smart production and Industry 4.0 principles depends on manufacturers' willingness and intention to adopt digital tools and technologies in their production processes [23]. Producers' intentions, attitudes, and behaviors regarding using digital tools in production processes reflect their subjective state.

Therefore, intention to use can be described as the user's belief and willingness to develop an attitude towards a certain object and manifest it through specific future behavior [24]. Also, behavioral intention determines the adoption of technological tools and the use of digitization [25]. Gajendragadkar et al. [26] examined how employees' behavioral intentions regarding digital learning platforms can influence the adoption of digitization, which will result in improved performance. In light of that, the following hypothesis was developed:

Hypothesis 1: Behavioral intention positively influences the use of digital platforms.

The desire to continue employing a particular technology is referred to as behavioral intention [27]. According to Moghavvemi et al.'s study [28], behavioral intention includes the choice of the individual to accept or reject the utilization of new technologies to improve business performance. It includes the interest of the individual or the desire to take part in particular technological activities [29]. Thun et al. [30] examined the relationship between operators' desire to implement Industry 4.0 technologies through digital tools and the requirement to create tools that will facilitate their operations. They point out the necessity of giving operators greater autonomy and authority in developing actions for the application of advanced technological tools. Also, Songkram et al. [31] emphasized that behavioral intention has a major impact on how digital learning platforms are employed, suggesting that higher adoption rates are associated with higher intentions to utilize these platforms. It is highlighted in a study by Venkatesh et al. [32] that the intention of users' behavior indicates the degree to which users intend to use digital learning platforms. The authors point out that the adoption of digital platforms depends primarily on the operator's intention to use them, but other specific factors, depending on the environment, affect the user's behavior intention to accept these platforms. In light of the demonstrated relationship between the concepts, the following hypothesis may be proposed:

Hypothesis 2: Intention to use digital platforms positively affects their adoption.

Given that new technologies are essential for digital transformation, many studies continue to emphasize that workers' attitudes are crucial for the successful adoption of Industry 4.0 [33]. Moreover, the adoption of digitization in the company depends on the attitude of the decision-makers [34]. The attitude towards digitization is a prerequisite for the acceptance of digital tools [35]. Also, in Cordero et al.'s study [36], it indicates attitudes toward innovation are essential to accepting digitization. According to the authors, attitude represents a positive or negative feeling towards adopting a certain technology. In manufacturing settings, digital systems are increasingly crucial as a link between humans and machines [37]. According to Thalmann et al.'s study [38], employee attitude towards digitalization and organizational culture are key to successfully facing the issues in smart manufacturing. For this purpose, employees must acquire the necessary knowledge to properly manage digitized production processes.

Hypothesis 3: Attitude towards digitization positively influences the use of digital platforms.

Industry 4.0 acceptance is essential for producers to stay competitive [39]. The defining feature of Industry 4.0 is the significant transformation in the interconnection of production systems, powered by the integration of machines into cyber-physical systems [40, 41]. Because of that, today, Industry 4.0 is considered a smart manufacturing era, as indicated by the use of connectivity digital platforms in the industry [42]. The acceptance of digital platforms positively influences the acceptance of Industry 4.0 technologies [39]. In this context, horizontal integration is one of the important features of Industry 4.0, referring to the complete connection of different processes and systems within an industry through digital technologies [40]. Integrated engineering systems have a crucial role in connecting people, devices, and systems through digital platforms to simplify collaboration between people, machines, and systems [43]. In addition, the role of Industry 4.0 technologies such as the IoT, big data analytics, 3D printing, robotics, advanced supply chain management, AI, 5G networks, and virtual reality (VR) in manufacturing companies is key to improving efficiency, productivity, and innovation [3, 4]. In light of all above factors, the following hypothesis was developed:

Hypothesis 4: Acceptance of digital platforms positively affects the adoption of Industry 4.0 technologies.

According to the proposed hypotheses, the conceptual model comprises five latent variables that can be seen in Figure 1.

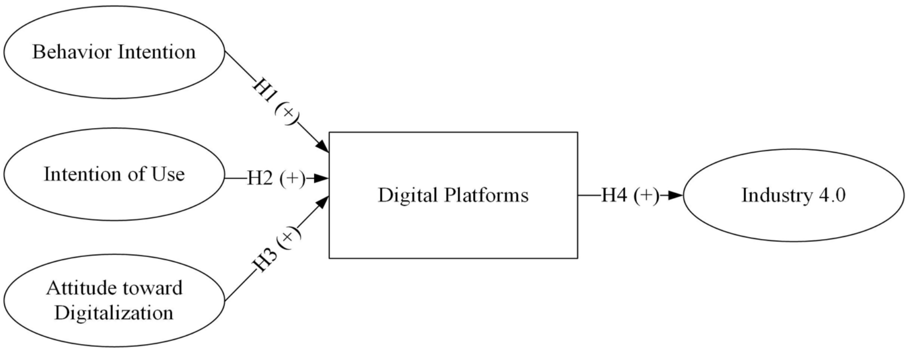

Figure 1. Conceptual model

3 Methodology

For research, a survey was conducted utilizing an online questionnaire. The managers and employees of production companies were given this questionnaire by personal email and the LinkedIn platform. The questionnaire consisted of two groups of questions. The first group involves the demographic characteristics of respondents, such as country, age, gender, level of education, years of work experience, and position in the company. The second group of questions explores behavioral intentions in the digital environment, intention to use digitization, attitudes toward digitization, use of digital platforms, and application of Industry 4.0 technologies. In this study, six countries-Serbia, Hungary, Poland, Slovakia, the Czech Republic, and Bulgaria-participated, providing a broad overview of digitalization in manufacturing companies. A total of 635 accurately completed questionnaires, of which Serbia (21.1%), Hungary

(17.3%), Poland (15.9%), Slovakia (15.7%), the Czech Republic (14.1%), and Bulgaria (15.9%). A five-point Likert scale was used to fill out the questionnaire. The demographic profile of respondents shows that the age group from 31 to 45 years is the most represented with 36.2%, while 23.9% of respondents were in the age range of 18 to 30 years, 32.1% of respondents were between 46 and 60 years old, and 7.7% of them were older than 61 years. In terms of gender, 61.9% of respondents were male, while 38.1% of participants were female. Regarding work experience, 28% of respondents had up to 5 years of work experience, 17.6% between 6 and 10 years, 23.5% between 11 and 20 years, while 30.9% had more than 20 years of work experience. Further on, the study processed and analyzed the data using statistical software SPSS v.25 and AMOS v.22.

4 Data Analysis and Results

For the research, SEM was utilized. This sophisticated statistical technique offers researchers the opportunity to evaluate and validate theoretical models [44]. SEM is used to model phenomena that are not directly measurable using latent variables that are derived from a larger set of observed variables [45, 46]. To model the latent variables based on the true values of these observed variables, it first separates measurement errors from the manifest variables values [47].

The SEM method contains a measurement model and a structural model. The measurement model includes the latent variables that contain the manifest variable variables [48]. The measurement model is evaluated to verify its validity and dependability. This includes examining the conceptual model's convergent and discriminant validity as well as internal consistency [49]. The structural model is assessed if the evaluation finds a suitable measurement model [48]. The developed hypotheses are tested by evaluating the structural model after the measurement model has been confirmed [50, 51]. Through a set of structural equations, which are equivalent to solving multiple regression equations, the structural model represents the relationships between latent and observable variables in the conceptual model [45].

The use of SEM method in this research will enable the examination of complex relationships between latent variables, which may contribute to a more precise understanding of the factors influencing digital transformation in the manufacturing industry.

4.1 Measurement Model

The first step in assessing a conceptual model is to create a measurement model. This requires the quantification of latent variables, which cannot be measured directly, utilizing observational indicators. Before conducting hypothesis testing on the structural model, it is important to first evaluate the measurement model to ensure the validity and reliability of the latent variables [44].

In this research, all latent variables have a unidimensional character and can be measured using a set of indicators connected to that dimension [44]. To enhance the accuracy and consistency of the measurement model, the model was adjusted iteratively based on assessing the conformance of the unidimensional model for each latent variable.

To assess the validity and reliability of the measurement model, it is necessary to establish whether the data fit the model well [44]. A good fit of the model in this study is indicated by the obtained normed χ^2 value (χ^2/df), which is also supported by other fit indices [50], the recommended and obtained values of which are displayed in Table 1.

Considering the satisfactory values of the fit parameters, the next step was to assess the convergent and discriminant validity of the constructs covered by the model. Convergent validity is evaluated through statistically significant factor loadings that should be greater than 0.50 [51]. The Average Variance Extracted (AVE) for each construct should be over 0.50 [46]. This means that a larger part of the variance in the indicators can be explained by the latent construct, indicating a satisfactory level of convergent validity.

Internal consistency coefficients, such as Cronbach's alpha and composite reliability, indirectly show the fulfillment of convergent validity conditions [52], whereas Nannally [53] suggested that values above 0.7 are considered satisfactory. However, according to George and Mallery's study [54], values above 0.6 are often considered acceptable, especially in the preliminary stages of research or when dealing with exploratory studies. Standardized factor loadings, reliability coefficients, and convergent validity are presented in Table 2.

Table 1. Fit indices for the measurement model

χ^2	χ^2/ df	RMSEA	CFI	NFI	TLI	IFI	RFI
$\chi^2 = 1176.48$; $\mathrm{df} = 500 (\mathrm{p} < 0.05)$	4.08	0.070	0.938	0.920	0.928	0.938	0.907
Accepted fit	< 3	< 0.08	> 0.90	> 0.90	> 0.90	> 0.90	> 0.90

To test for discriminant validity, the AVE for each underlying concept should be compared with the squared correlations between those concepts. If the AVE values for each concept are higher than the squared correlations between concepts, then the conditions for discriminant validity are met. The AVE values and squared correlations between concepts are displayed in Table 3, and it can be deduced that the discriminant validity has been confirmed.

Table 2. Results of the measurement model

Variables	Standardized Factor Loading	Critical Ratio (t-value)	AVE	Cronbach ALFA	CR	P
Behavior Intention (BI)						
Q1 Intention for greater digitization of processes	0.903					
Q2 Anticipating future digitization	0.942	39.409	0.846	0.942	0.943	****
Q3 Plans for investing in digitization	0.915	36.885				
Intention of Use (IU)						
Q1 Work in a digitized environment	0.906					
Q2 Using digital tools to access materials	0.889	33.480	0.812	0.928	0.928	***
Q3 Using digitized processes at work	0.908	35.010				
Attitudes Towards Digitization (ATD)						
Q1 Digitization is a good idea	0.788					
Q2 Digitization makes work more interesting	0.816	22.217				
Q3 Working in a digitized environment is fun	0.734	19.496	0.633	0.895	0.895	****
Q4 I like the digitized work environment	0.827	22.602				
Q5 Digitization creates a competitive advantage	0.810	22.021				
Digital Platforms (DP)						
Q1 Use of a professional digital platform	0.650					
Q2 Use of professional digitalized communication tools	0.773	12.913	0.410	0.660	0.667	***
Q3 Use of social networking for business purposes	0.458	9.392				
Industry 4.0 (I4.0)						
Q1 Cloud computing services	0.598					
Q2 Big data analysis	0.772	15.312				
Q3 3D printing and robotics	0.734	14.794				
Q4 Internet of Things	0.743	14.922	0.574	0.911	0.915	****
Q5 Virtual reality	0.838	16.147				
Q6 Augmented reality	0.847	16.251				
Q7 Supply chain management	0.696	14.248				
Q8 Artificial intelligence	0.807	15.768				

Table 3. Correlation matrix and discriminant validity ($p < 0.01$)

	Behavior Intention	Intention of Use	Attitudes Towards Digitization	Digital Platforms	Industry 4.0
Behavior Intention	**0.919**				
Intention of Use	0.621**	**0.901**			
Attitudes Towards Digitization	0.606**	0.638**	**0.795**		
Digital Platforms	0.465**	0.439**	0.430**	**0.640**	
Industry 4.0	0.396**	0.439**	0.430**	0.392**	**0.757**

4.2 Structural model

At first, a test was performed to assess how well the structural model fits the observed data. The obtained values of χ^2 (χ^2/df=2.914; $p < 0.05$) indicate a good fit of the structural model to this study's data, as recommended by George and Mallery [54]. Also, other fit indices such as RMSEA=0.070, CFI=0.937, NFI=0.919, IFI=0.937, and RFI=0.907 confirm the good fit of the model [55]. Table 4 and Figure 2 show the results of structural model estimation, where beta coefficients represent the size of the effect of one latent variable on another, while t-values test the statistical significance of those effects. In this model, all proposed hypotheses show a positive direction and statistical significance, confirming that the data support the hypothesized relationships between the latent variables. In this model, all proposed hypotheses show a positive direction and exhibit statistical significance, confirming that the data support the hypothesized relationships between the latent variables. Behavior intention positively affects the digital platforms (β = 0.333, t=5.344, $p < 0.01$), which indicates that hypothesis H1: BI→DP is accepted. The obtained results verify the positive impact of the intention of use on digital platforms at a 99% confidence interval (β=0.279, t=4.189, $p < 0.01$). Consequently, the hypothesis H2: IU→DP is accepted. Also, the findings confirm that there is significant evidence predicting the impact of attitudes towards digitization on digital platforms at a 95% confidence interval (β=0.151, t=2.250, $p < 0.05$), indicating the hypothesis H3: ATD→DP, which is also confirmed. Finally, the construct composed of digital platform use proved to be a good predictor of the application of Industry 4.0 technologies, highlighting that the obtained findings have statistical significance at a 99% confidence interval (β= 0.556, t= 9.213, $p < 0.01$). This proves that hypothesis H4: DP→I4.0 is supported. The positive path coefficients and significant t-values collectively indicate that the model adequately reflects the theoretical assumptions, confirming all the hypotheses posited in the study (Table 4).

Table 4. Path coefficients and t-values

The Relationship or Path	Standardized Parameters	t-value	Causal Relations
H1: Behavior Intention - Digital Platforms	0.333	5.344 (a)	R1: yes
H2: The Intention of Use - Digital Platforms	0.279	4.189 (a)	R1: yes
H3: Attitudes Towards Digitization - Digital Platforms	0.151	2.250 (b)	R1: yes
H4: Digital Platforms - Industry 4.0	0.556	9.213 (a)	R1: yes

Note: (a) Significant at the 99% level; (b) Significant at the 95% level

Table 5. Structural analysis results

Variables	n	Standardized Factor Loading	Critical Ratio or (t-value)	R^2
Behavior Intention (BI)				
Q1 Intention for greater digitization of processes	3	0.903		/
Q2 Anticipating future digitization		0.942	390.414	
Q3 Plans for investing in digitization		0.915	360.884	
Intention of Use (IU)				
Q1 Work in a digitized environment	3	0.906		/
Q2 Using digital tools to access materials		0.889	330.471	
Q3 Using digitized processes at work		0.908	350.034	
Attitudes Towards Digitization (ATD)				
Q1 Digitization is a good idea	5	0.788		/
Q2 Digitization makes work more interesting		0.816	220.216	
Q3 Working in a digitized environment is fun		0.734	190.488	
Q4 I like the digitized work environment		0.828	220.604	
Q5 Digitization creates a competitive advantage		0.810	220.014	
Digital Platforms (DP)				
Q1 Use of a professional digital platform	3	0.637		0.460
Q2 Use of professional digitalized communication tools		0.779	130.144	
Q3 Use of social networking for business purposes		0.467	90.311	
Industry 4.0 (I4.0)				
Q1 Cloud computing services	8	0.596	150.234	0.310
Q2 Big data analysis		0.771	140.725	
Q3 3D printing and robotics		0.733	140.851	
Q4 Internet of Things		0.742	160.086	
Q5 Virtual reality		0.840	160.192	
Q6 Augmented reality		0.849	140.185	
Q7 Supply chain management		0.695	150.710	
Q8 Artificial intelligence		0.808	150.234	

Table 5 shows the standardized loading factors and determination coefficient (R^2). The effect of independent latent variables such as behavior intention, intention of use, and attitude toward digitalization on the dependent latent variable, digital Platform, was examined. The coefficient of determination for this relationship was estimated at 46.0% of the explained variance of the digital platform, while for the latent variable of Industry 4.0, it was 31.0%.

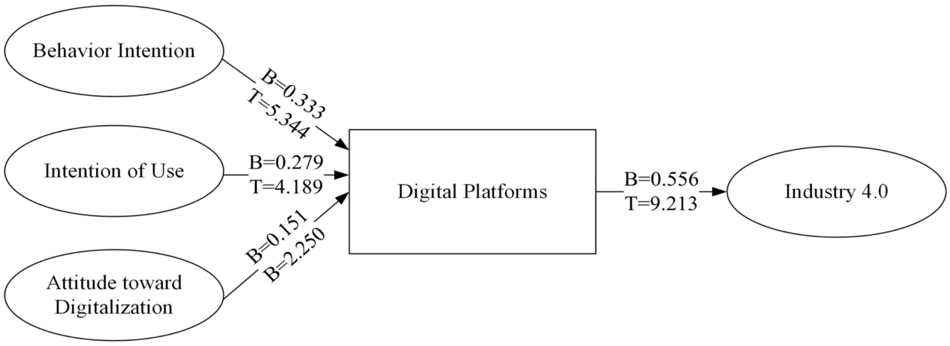

Figure 2. Structural model

5 Discussion

In this research, the influence of three dimensions—behavior intention in the digital environment, intention to use digitization, and attitudes towards digitization—on the application of digital platforms, which leads manufacturing companies to digital transformation, is analyzed in the era of Industry 4.0. To examine the influence between the defined constructs, a questionnaire in online form was used. It was collected from 635 correctly filled-out questionnaires by e-mail and via the LinkedIn platform, and six countries—Serbia, Hungary, Poland, Slovakia, the Czech Republic, and Bulgaria—participated in the research. The focus on these countries is justified due to their key role in the transition to more advanced production practices in Central and Eastern Europe in the context of the adoption of Industry 4.0 technologies. These countries represent diverse economic and technological frameworks that influence the implementation and adaptation of Industry 4.0. Therefore, by applying the SEM methodology used in this research, more concrete conclusions can be drawn.

In hypothesis H1, it was supposed that behavioral intention positively influences the use of digital platforms, and results indicate that hypothesis H1: BI→DP is accepted. Confirmable findings can be found in the research of authors [24], who investigated how employees' behavioral intentions influence the use of digital learning platforms, which in turn has an impact on digitization adoption. According to the results of the SEM analysis, intention of use significantly affects digital platforms, indicating that hypothesis H2: IU→DP is also accepted. Similar findings can be found in the literature, describing how behavioral intention reflects the extent to which users plan to use digital platforms, suggesting that higher intention to use these platforms leads to higher adoption rates [31, 32]. The findings confirm that there is a significant impact of attitudes towards digitization on digital platforms, pointing out that hypothesis H3: ATD→DP is confirmed. Taking into account the confirmed relationship in this research, it can be seen that it is in line with many previous studies that emphasize that workers' attitudes are crucial for the successful adoption of digital tools [35, 36, 38]. Using digital platforms is often shown to be a good predictor of the application of Industry 4.0 technologies. In this context, the hypothesis H4: DP → I4.0 is supported. Digital platforms enable the integration and automation of various aspects of production and operations, which is an essential part of Industry 4.0. Using digital platforms can make progress in companies' ability to apply and utilize technologies such as IoT, artificial intelligence, integration, big data analytics, 3D printing, and robotics, which are central to Industry 4.0 [3, 4, 39].

The findings of this research significantly contribute to the theoretical and practical understanding of digital transformation in manufacturing companies, providing deep insights into how dimensions such as behavioral intention, intention to use, and attitudes towards digitization influence the application of digital platforms and then how these platforms influence the adoption of Industry 4.0 technologies. The research provides key insights into how various factors influence the success of digital transformation in manufacturing companies, which can help shape policies and practices that encourage more effective adoption of Industry 4.0 technologies.

6 Conclusions

This research provides significant insights into the impact of three key dimensions – behavioral intentions in the digital environment, intentions to use digitization and attitudes towards digitization – on the implementation of digital platforms, leading to the digital transformation of manufacturing companies in the era of Industry 4.0. Applying the SEM methodology to a sample of 635 respondents from six countries (Serbia, Hungary, Poland, Slovakia, the Czech Republic, and Bulgaria), all hypotheses were confirmed, highlighting the key factors influencing the successful adoption of digital platforms and Industry 4.0 technologies. Accordingly, the research provides insight into different perspectives and levels of acceptance of digital platforms and Industry 4.0 technologies in different cultural and economic environments.

The theoretical implications of this research confirm the existing literature that highlights the importance of behavioral intention and employees' attitudes for the successful adoption of digital technologies. The research expands the understanding of these constructs in the context of manufacturing companies, offering new insights into the digital transformation process. Practical implications include specific recommendations for managers and decision-makers in manufacturing companies. The results suggest that it is essential to focus on strengthening employees' positive attitudes toward digitization and increasing their intention to use digital tools. This can significantly accelerate the adoption of digital platforms and technologies that are key to the successful implementation of Industry 4.0, enabling companies to improve their efficiency and competitiveness in a global environment.

Limitations of this study include a focus on only six countries, which may limit the generalizability of the results globally, as well as potential cultural and economic variations that were not fully accounted for. The use of online questionnaires and email distributions may lead to sample bias, as only those individuals who are already digitized may have participated. Future research could expand the scope of the study to a larger number of countries and different industry sectors to gain a broader insight into the factors influencing digital transformation. Also, combining quantitative and qualitative methods could provide a deeper understanding of the motivations and barriers to adopting digital technologies.

Funding

The article was funded by the Science Fund of the Republic of Serbia (Grant No.: 5151), Support Systems for Smart, Ergonomic and Sustainable Mining Machinery Workplaces – Smart Miner and the Ministry of Science, Technological Development and Innovation (Grant No.: 451-03-65/2024-03/200105; 451-03-66/2024-03/200109).

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Acknowledgements

This article is based upon work from COST Action CA22124 - ECO4ALL "EU Circular Economy Network for All: Consumer Protection Through Reducing, Reusing, Repairing", supported by COST (European Cooperation in Science and Technology - www.cost.eu).

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] A. Zangiacomi, E. Pessot, R. Fornasiero, M. Bertetti, and M. Sacco, "Moving towards digitalization: A multiple case study in manufacturing," *Prod. Plann. Control*, vol. 31, no. 2-3, pp. 143–157, 2020. https://doi.org/10.1080/09537287.2019.1631468

[2] S. Erol, A. Jäger, P. Hold, K. Ott, and W. Sihn, "Tangible Industry 4.0: A scenario-based approach to learning for the future of production," *Procedia CIRP*, vol. 54, pp. 13–18, 2016. https://doi.org/10.1016/j.procir.2016.03.162

[3] K. Rong, "Research agenda for the digital economy," *J. Digit. Econ.*, vol. 1, no. 1, pp. 20–31, 2022. https://doi.org/10.1016/j.jdec.2022.08.004

[4] N. Urbach, F. Ahlemann, T. Böhmann, P. Drews, W. Brenner, F. Schaudel, and R. Schütte, "The impact of digitalization on the IT department," *Bus. Inf. Syst. Eng.*, vol. 61, pp. 123–131, 2019. https://doi.org/10.1007/s12599-018-0570-0

[5] D. Horvat, H. Kroll, and A. Jäger, "Researching the effects of automation and digitalization on manufacturing companies' productivity in the early stage of Industry 4.0," *Procedia Manuf.*, vol. 39, pp. 886–893, 2019. https://doi.org/10.1016/j.promfg.2020.01.401

[6] L. Silvestri, A. Forcina, V. Introna, A. Santolamazza, and V. Cesarotti, "Maintenance transformation through Industry 4.0 technologies: A systematic literature review," *Comput. Ind.*, vol. 123, p. 103335, 2020. https://doi.org/10.1016/j.compind.2020.103335

[7] P. Schneider, "Managerial challenges of Industry 4.0: An empirically backed research agenda for a nascent field," *Rev. Manag. Sci.*, vol. 12, no. 4, pp. 803–848, 2018. https://doi.org/10.1007/s11846-018-0283-2

[8] D. P. Sakas, N. T. Giannakopoulos, M. C. Terzi, N. Kanellos, and A. Liontakis, "Digital transformation management of supply chain firms based on big data from DeFi social media profiles," *Electronics*, vol. 12, no. 20, p. 4219, 2023. https://doi.org/10.3390/electronics12204219

[9] G. B. Benitez, A. Ghezzi, and A. G. Frank, "When technologies become Industry 4.0 platforms: Defining the role of digital technologies through a boundary-spanning perspective," *Int. J. Prod. Econ.*, vol. 260, p. 108858, 2023. https://doi.org/10.1016/j.ijpe.2023.108858

[10] J. Cenamor, V. Parida, and J. Wincent, "How entrepreneurial SMEs compete through digital platforms: The roles of digital platform capability, network capability and ambidexterity," *J. Bus. Res.*, vol. 100, pp. 196–206, 2019. https://doi.org/10.1016/j.jbusres.2019.03.035

[11] A. Ahmed, S. H. Bhatti, I. Gölgeci, and A. Arslan, "Digital platform capability and organizational agility of emerging market manufacturing SMEs: The mediating role of intellectual capital and the moderating role of environmental dynamism," *Technol. Forecast. Soc. Change*, vol. 177, p. 121513, 2022. https://doi.org/10.1016/j.techfore.2022.121513

[12] A. G. Frank, G. H. Mendes, N. F. Ayala, and A. Ghezzi, "Servitization and Industry 4.0 convergence in the digital transformation of product firms: A business model innovation perspective," *Technol. Forecast. Soc. Change*, vol. 141, pp. 341–351, 2019. https://doi.org/10.1016/j.techfore.2019.01.014

[13] S. Chatterjee, N. P. Rana, Y. K. Dwivedi, and A. M. Baabdullah, "Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model," *Technol. Forecast. Soc. Change*, vol. 170, p. 120880, 2021. https://doi.org/10.1016/j.techfore.2021.120880

[14] A. Stark, K. Ferm, R. Hanson, M. Johansson, S. Khajavi, L. Medbo, and J. Holmström, "Hybrid digital manufacturing: Capturing the value of digitalization," *J. Oper. Manag.*, vol. 69, no. 6, pp. 890–910, 2023. https://doi.org/10.1002/joom.1231

[15] A. Jamwal, R. Agrawal, and M. Sharma, "Challenges and opportunities for manufacturing SMEs in adopting Industry 4.0 technologies for achieving sustainability: Empirical evidence from an emerging economy," *Oper. Manag. Res.*, pp. 1–26, 2023. https://doi.org/10.1007/s12063-023-00428-2

[16] Y. X. Duan, "Can digital empowerment enhance the brand value of China's enterprises?" *Technol. Anal. Strateg. Manag.*, vol. 34, no. 1, pp. 1–15, 2024. https://doi.org/10.1080/09537325.2024.2358444

[17] R. Y. Zhong, X. Xu, E. Klotz, and S. T. Newman, "Intelligent manufacturing in the context of Industry 4.0: A review," *Eng.*, vol. 3, no. 5, pp. 616–630, 2017. https://doi.org/10.1016/J.ENG.2017.05.015

[18] W. Urban, K. Lukaszewicz, and E. Krawczyk-Dembicka, "Application of Industry 4.0 to the product development process in project-type production," *Energies*, vol. 13, no. 21, p. 5553, 2020. https://doi.org/10.3390/en13215553

[19] A. Kusiak, "Smart manufacturing," *Int. J. Prod. Res.*, vol. 56, no. 1-2, pp. 508–517, 2018. https://doi.org/10.1080/00207543.2017.1351644

[20] M. Ghobakhloo, "Determinants of information and digital technology implementation for smart manufacturing," *Int. J. Prod. Res*, vol. 58, no. 8, pp. 2384–2405, 2020. https://doi.org/10.1080/00207543.2019.1630775

[21] P. Aghion and R. Griffith, "Innovation and inequalities," Institute for Fiscal Studies, 2022. https://ifs.org.uk/inequality/wp-content/uploads/2022/03/Innovation-and-inequalities-IFS-Deaton-Review-Inequalities.pdf

[22] N. Sinha and A. Kumar, "Challenges in implementation of Industry 4.0 in manufacturing sector," in *Next Generation Materials and Processing Technologies*. Singapore: Springer, 2021. https://doi.org/10.1007/978-981-16-0182-8_44

[23] T. Schøtt, Ö. Kunday, F. Boutaleb, E. Menipaz, W. A. Rahman, C. Bouhaddioui, F. Pereira, and M. A. Grijalba, "Intention to adopt digital technology in businesses: Promoted by early and recent digitalization and embedded in societal and temporal contexts," *Int. Rev. Entrep.*, vol. 20, no. 3, pp. 423–446, 2022.

[24] M. Fishbein and I. Ajzen, *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Massachusetts, USA: Addison-Wesley Publishing Company, 1975.

[25] G. Zacharis and K. Nikolopoulou, "Factors predicting university students' behavioral intention to use elearning platforms in the post-pandemic normal: An UTAUT2 approach with 'Learning Value'," *Educ. Inf. Technol.*, vol. 27, pp. 12 065–12 082, 2022. https://doi.org/10.1007/s10639-022-11116-2

[26] S. Gajendragadkar, R. Arora, R. Trivedi, and N. Neelam, "From intentions to action: How behavioural intentions shape employee performance through digital learning," *J. Workplace Learn.*, vol. 36, no. 5, pp. 348–363, 2024. https://doi.org/10.1108/jwl-02-2024-0021

[27] R. Basuki, Z. J. H. Tarigan, H. Siagian, L. S. Limanta, D. Setiawan, and J. Mochtar, "The effects of perceived ease of use, usefulness, enjoyment and intention to use online platforms on behavioral intention in online movie watching during the pandemic era," *Int. J. Data Netw. Sci.*, vol. 6, pp. 253–262, 2022. https://doi.org/10.5267/j.ijdns.2021.9.003

[28] S. Moghavvemi, N. A. Salleh, and C. Standing, "Entrepreneurs adoption of information system innovation: The impact of individual perception and exogenous factors on entrepreneurs behavior," *Internet Res.*, vol. 26, no. 5, pp. 1181–1208, 2016. https://doi.org/10.1108/IntR-01-2014-0024

[29] M. Hubert, M. Blut, B. Christian, R. W. Zhang, V. Koch, and R. Riedl, "The influence of acceptance and adoption drivers on smart home usage," *Eur. J. Mark.*, vol. 53, no. 6, pp. 1073–1098, 2019. https://doi.org/10.1108/EJM-12-2016-0794

[30] S. Thun, P. F. Kamsvåg, B. Kløve, E. A. Seim, and H. Y. Torvatn, "Industry 4.0: Whose revolution? The digitalization of manufacturing work processes," *Nord. J. Work. Life Stud.*, vol. 9, no. 4, pp. 42–61, 2019.

https://doi.org/10.18291/njwls.v9i4.117777
[31] N. Songkram, S. Chootongchai, H. Osuwan, Y. Chuppunnarat, and N. Songkram, "Students' adoption towards behavioral intention of digital learning platform," *Educ. Inf. Technol.*, 2023. https://doi.org/10.1007/s10639-023-11637-4
[32] V. Venkatesh, M. G. Morris, G. B. Davies, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Q.*, vol. 27, no. 3, pp. 425–478, 2003. https://doi.org/10.2307/30036540
[33] H. E. Chueh and D.-H. Huang, "Usage intention model of digital assessment systems," *J. Bus. Res.*, vol. 156, p. 113469, 2023. https://doi.org/10.1016/j.jbusres.2022.113469
[34] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User acceptance of computer technology: A comparison of two theoretical models," *J. Manag. Sci.*, vol. 35, no. 8, pp. 982–1003, 1989.
[35] L. Bollweg, R. Lackes, M. Siepermann, and P. Weber, "Drivers and barriers of the digitalization of local owner-operated retail outlets," *J. Small Bus. Entrep.*, vol. 32, no. 2, pp. 173–201, 2020. https://doi.org/10.1080/08276331.2019.1616256
[36] D. Cordero, K. L. Altamirano, J. O. Parra, and W. S. Espinoza, "Intention to adopt Industry 4.0 by organizations in Colombia, Ecuador, Mexico, Panama, and Peru," *IEEE Access*, vol. 11, pp. 8362–8386, 2023. https://doi.org/10.1109/ACCESS.2023.3238384
[37] H. ElMaraghy, L. Monostori, G. Schuh, and W. ElMaraghy, "Evolution and future of manufacturing systems," *CIRP Annals*, vol. 70, no. 2, pp. 635–658, 2021. https://doi.org/10.1016/j.cirp.2021.05.008
[38] S. Thalmann, A. Fessl, and V. Pammer-Schindler, "How large manufacturing firms understand the impact of digitization: A learning perspective," in *53rd Hawaii International Conference on System Sciences*, 2020, pp. 1–10.
[39] S. Parhi, K. Joshi, T. Wuest, and M. Akarte, "Factors affecting Industry 4.0 adoption – A hybrid SEM-ANN approach," *Comput. Ind. Eng.*, vol. 168, p. 108062, 2022. https://doi.org/10.1016/j.cie.2022.108062
[40] L. S. Dalenogare, G. B. Benitez, N. Ayala, and A. G. Frank, "The expected contribution of Industry 4.0 technologies for industrial performance," *Int. J. Prod. Econ.*, vol. 204, pp. 383–394, 2018. https://doi.org/10.1016/j.ijpe.2018.08.019
[41] K. Schwab, *The Fourth Industrial Revolution*. Crown Currency, 2017.
[42] G. Reischauer, "Industry 4.0 as policy-driven discourse to institutionalize innovation systems in manufacturing," *Technol. Forecast. Soc. Change*, vol. 132, pp. 26–33, 2018. https://doi.org/10.1016/j.techfore.2018.02.012
[43] H. Kagermann, W. Wahlster, and J. Helbig, "Recommendations for implementing the strategic initiative INDUSTRIE 4.0," Acatech — National Academy of Science and Engineering, 2013.
[44] J. C. Anderson and D. W. Gerbing, "Structural equation modeling in practice: A review and recommended two-step approach," *Psychol. Bull.*, vol. 103, no. 3, pp. 411–423, 1988. https://doi.org/10.1037/0033-2909.103.3.411
[45] J. B. Schreiber, A. Nora, F. K. Stage, E. A. Barlow, and J. King, "Reporting structural equation modelling and confirmatory factor analysis results: A review," *J. Educ. Res.*, vol. 99, no. 6, pp. 323–337, 2006. https://doi.org/10.3200/JOER.99.6.323-338
[46] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *J. Mark. Res.*, vol. 18, no. 1, pp. 39–50, 1981. https://doi.org/10.1177/002224378101800104
[47] K. H. Yuan and P. M. Bentler, "10 structural equation modeling," in *Handbook of Statistics*, 2006, pp. 297–358. https://doi.org/10.1016/S0169-7161(06)26010-3
[48] M. E. Civelek, *Essentials of Structural Equation Modeling*. Nebraska, USA: Zea Books, 2018.
[49] D. W. Ko and W. P. Stewart, "A structural equation model of residents' attitudes for tourism development," *Tour. Manag.*, vol. 23, no. 5, pp. 521–530, 2002. https://doi.org/10.1016/S0261-5177(02)00006-7
[50] B. M. Byrne, "Testing for multigroup invariance using graphics: A road less traveled," *Struct. Equ. Model. A Multidiscip. J.*, vol. 11, no. 2, pp. 272–300, 2004. https://doi.org/10.1207/s15328007sem1102_8
[51] J. F. Hair, R. E. Anderson, R. L. Tatham, and W. Black, *Multivariate Date Analysis*. New Jersey, USA: Prentice-Hall, 1998.
[52] L. J. Cronbach, "Coefficient alpha and the internal structure of tests," *Psychometrika*, vol. 16, pp. 297–334, 1951. https://doi.org/10.1007/BF02310555
[53] J. C. Nannally, *Psychometric Theory*. New York, USA: McGraw-Hill, 1978.
[54] D. George and P. Mallery, "Frequencies," in *IBM SPSS Statistics 23 Step by Step*. New York, USA: Routledge, 2016, pp. 115–125.
[55] T. A. Brown, *Confirmatory Factor Analysis for Applied Research*. New York, USA: Guilford Press, 2006.