

Article

Investigation of the Industry 4.0 Technologies Adoption Effect on Circular Economy

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Abstract: Industry 4.0 technologies' adoption became a reality in manufacturing and other industrial companies. The effects of this adoption on several areas including the Circular Economy are interesting in the research field. Deep research and investigation of various Industry 4.0 technologies' relationships with the Circular Economy are presented in this article. The investigation is based on collected data from 798 companies in five countries, Lithuania, Slovakia, Austria, Croatia, and Slovenia as part of the European Manufacturing Survey project in 2018. After filtering the data, groups' comparison is used to form potential prospective relationships in connection with the presented literature. A logistics regression test is used by SPSS software to validate the hypotheses and potential relations. Based on the achieved results, it seems that both Industry 4.0 and non-Industry 4.0 technologies can have significant relations with Circular Economy technologies, so they can be potentially influenced or enhanced by both. Similarly, an investigation of the relations between the development of products with improved environmental impact and the use of Industry 4.0 technologies showed no clear dominance of Industry 4.0 technologies over non-Industry 4.0. Finally, there are two of the twelve investigated technologies that have a significant relationship (potential impact) on both the Circular Economy technologies and product development with improved environmental impact.

Keywords: Industry 4.0; Circular Economy manufacturing company; survey analysis



Citation: Akkad, M.Z.; Šebo, J.; Bányai, T. Investigation of the Industry 4.0 Technologies Adoption Effect on Circular Economy. *Sustainability* **2022**, *14*, 12815. <https://doi.org/10.3390/su141912815>

Academic Editors: Ting Chi and Babu John-Mariadoss

Received: 30 August 2022

Accepted: 5 October 2022

Published: 8 October 2022

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1. Introduction

Industry 4.0 (I4.0) represents several applications and technologies that provide various possible positive impacts on the industrial and logistics areas through supporting various practices that include Circular Economy (CE) [1]. Despite the promising potential of I4.0 technologies, there is a need to understand their effects on the manufacturing companies' outcomes in action. A study aimed to understand the patterns of I4.0 technologies' adoption in manufacturing firms [2] showed that companies that have an advanced implementation level of I4.0 tend to use the majority of the front-end technologies rather than a specific subset. Additionally, the I4.0 framework was applied to raise the efficiency of energy and maintenance in a chemical plant where significant reductions (around 50%) in energy consumption and needed inspections for maintenance, next to less replacement time for the used pieces, were achieved with a rational cost [3]. Management systems for energy and maintenance were integrated into the supply chain management system and the overall company management systems. Collected information by these management systems supported the process of decision-making. For the aspect of reuse and disassembly, a scientific gap in researching those two actions was mentioned [4].

Based on the resulting literature [4], cyber-physical systems (CPSs), Internet of Things (IoT), big data and analytics (BDA), additive manufacturing (AM), and simulation were specified as prime I4.0 technologies attached to the CE. On the other hand, the only paper found by a systematic literature review (SLR) that focused on reuse strategies considered AM the main solution for raising reuse efficiency [5]. In that case, reusing was intended

for the terms of facilitating the textiles disassembly and reassembly. In the conclusion of that analytical work, AM and the IoT were the most mentioned as digital enablers for the CE. CPSs were taken as valid assisting tools to develop innovative lifecycle and product management strategies as well [4]. For instance, a study presented a cyber-physical system that adopted IoT and data collection and analysis where the system was designed and presented to optimize multi-echelon collection and distribution operations with a focus on energy efficiency, sustainability, and emission reduction [6].

In a study in 2021 [7] that used a survey that aimed at 120 project managers, and 27 projects about the I4.0 technologies effects on the CE, AM showed one of the greatest influences on CE, as an assumption, because it was more difficult to estimate the other I4.0 technologies' impact to determine that contribution as a value. The necessity of developing other quantitative studies that embrace the industrial companies that use I4.0 technologies as a combination in their processes and that have a synergistic impact on CE was also mentioned. Because although a few technologies appear to have a greater positive impact than others on individual bases, it appears important to consider the combined effect to measure the real influence on CE, however, the complexity of such multiple cases can limit its results. The results show the existence of various effects that I4.0 technologies bring to companies that contribute to circularity. The developments are mainly concerned with reducing the consumed material and energy, waste, and emissions generation. However, each technology showed noticeable different potential impacts. Especially, AM and robots showed a higher positive impact [7].

Our study brings new light to this discussion of whether I4.0 technologies have a potential influence on the use of CE technologies in manufacturing companies. It also reveals if the use of these I4.0 technologies has a relation (potential influence) to the new product development, especially when the improved environmental impact of the product is the case. Moreover, the used data provided the possibility of including non-I4.0 technologies and allowed us to conduct a comparison of whether I4.0 or non-I4.0 technologies have a bigger potential to influence the adoption of CE technologies in manufacturing companies. This study is divided into four chapters. Chapter one presents an introduction to the impact of I4.0 technologies on CE. Chapter two discusses the theoretical background of CE and main I4.0-related technologies as a literature review that summarizes the main academic contribution in this area. Chapter three shows the methodology and data that were adopted in this study next to statistical analysis to validate the hypotheses and discusses their results. The data sample is collected within the European Manufacturing Survey (EMS) project. Chapter four shows the reached conclusions and their possible impact in light of the previous studies.

2. Theoretical Background

This chapter presents a theoretical background of this study. Mainly, the CE concept and the I4.0 technologies related to CE are to be discussed.

2.1. Circular Economy

CE represents a business mindset to assist companies and communities in moving toward sustainability [8]. It provides an alternative viewpoint on the operational and formal frameworks of producing and consuming that is focused on re-establishing the estimation of used assets. CE suggests using a roundabout path to treat the materials that are possible to provide financial, sustainable, and social advantages [9] to organizations and replacing the conventional style of 'take, make, use and dispose', which is recognized as the linear economy. However, applying CE concepts and standards in companies and manufacturing practices may face obstructions that cause more limitations than the fully expected results [10]. For instance, in a study of the CE implementation in China [11], the following challenges to a successful implementation of the CE were identified: a shortage of credible information, lack of state-of-art technology, weak legislation enforced, low economic rewards, weak leadership and management, and shortage of public awareness.

Regarding materials utilization [12], CE is a growing paradigm that aims to achieve sustainable utilization of natural resources [8]. It concentrates on increasing the resources' circularity within manufacturing systems, because raw resources are limited, and the waste even at the end of its life can hold a value [13]. CE is primarily based on two cycles that are technical and biological [14]. The technical cycle emphasizes the growth of a product's life anticipation by a fast order of circular systems that include reusing, repairing, refurbishment, remanufacturing, and recycling [15]; this cycle is also looking to convert what is as identified waste into inputs for other forming frameworks. The biological cycle supports the environment by reducing the gross extraction of raw assets, using the materials in a sustainable way, and adopting anaerobic assimilation methods in waste management [16,17]. CE can be represented with three principles as well. These three principles are protecting regular raw capital for achieving a balance for usage amongst sustainable and non-renewable assets, increasing the expected life for the assets by both natural and specialized ways, and reducing the unfavorable effects of production substructures [1]. The following six business actions that are referred to by the ReSOLVE framework were presented by Ellen MacArthur Foundation [14]. ReSOLVE refers to Regenerate, Share, Optimize, Loop, Virtualize, and Exchange, which are used to direct organizations through the fulfillment of the CE principles.

2.2. Industry 4.0

Industrial revolution expression symbolizes a volume industrial leap. This means the increase of quality, quantity, or both by implementing innovative industrial methods via new tools and technologies [18]. Until recently, three industrial revolutions were identified. We are now starting to talk about Fifth Industrial Revolution (Industry 5.0) but still, especially in central European countries, in the middle of the Fourth one, as known as "Industry 4.0", which is totally dominating the industrial areas [19]. I4.0 tools contain the most novel technologies that are based particularly on internet, telecommunications, and nanotechnology that enabled us to utilize smaller devices with higher efficiency. The combination of the mentioned technologies allowed the development of a wide range of applications and tools that revolutionized the industry by transforming the conventional idea of the connection between human and machine into the machine and machine communication concept [20,21]. The rapid industrial development is a notice that pushes us to eagerly pursue the new I4.0 applications, so we can keep pace with this evolution and apply it in our area of specialization [22] such as CE development. The rate of industrial growth is continuously increasing. The technological developments next to intelligent tools based on the internet show results in various software areas ranging from CAD modeling [23] to the solution of digital twinning [24]. As a classification of I4.0, nine technologies were the major blocks of I4.0 [25]: BDA, autonomous robots and vehicles, AM, simulation, augmented and virtual reality, horizontal/vertical system integration, the IoT, cloud, fog, and edge technologies, and blockchain and cyber-security.

Considering the expected influence of I4.0 technologies on CE, six commonly identified I4.0 technologies in the literature are to be presented in more detail in various industrial aspects. Other technologies were even mentioned but there were no more relevant studies found that support more details about their possible impact on CE.

2.2.1. Additive Manufacturing

Thirty articles identified AM as a reference element for the relationships between I4.0 and CE [4]. It mainly described how AM can help to manage the products' lifecycle and processes while only a few considerations were mentioned for other connections. Also, few researchers discussed AM use to improve existing recycling processes by new sustainable networks using and manufacturing process digitizing, for instance, through a new type of process [26] or managerial strategies [27]. Others proposed AM utilization concept for supporting the products or components remanufacturing [28,29], circular

business model development that centered on recycled materials [30], and the reuse of products/materials [5].

2.2.2. Internet of Things

IoT is regarded as a very important technology that is capable of facilitating the transition into CE [4]. Apart from the papers that focused on a general potential description for the IoT to extend the product life cycle, there was a mutual realization that IoT extends its potential influence on a broad number of areas related to CE. One of the options was to adopt the IoT for smart cities strategies in innovative waste management [31]. Another option was to improve the metallurgical processes' circularity level [32]. Additionally, an opportunity for leveraging the IoT was CE digitization practices, for instance, implementing environments for smart industry [33] or control loops with dynamic feedback [34].

2.2.3. Simulation

Numerous studies were conducted to investigate the simulations' effects on circular business models and product lifecycle management [4]. Other studies identified various ways where simulation can support the CE. For instance, material flow modeling [35] or using simulation tools to support the decision of products' remanufacturing [36,37]. In a case study, simulation was discussed as a supporting tool in recycling for calculating the performance indexes of recycling [38].

2.2.4. Big Data and Analytics

BDA was considered an easy way to digitize the CE [39]. However, the possibilities of this way varied in many directions. For instance, developing automated assessments of the potential secondary materials value [40], using open-source tools, open data, procedures, and services for encouraging the action of reusing [41], and the service of cloud platforms for data collection and analysis [42]. Additionally, BDA was considered within the integrative frameworks in innovative business models [43] for managing the products' lifecycle [44] or implementing smart manufacturing activities [45], as well as improving disassembly sequence planning [46] and recycling issues during product design [47].

2.2.5. Robots

In a study about human-robot collaboration [48], a recycling line that is used for computer cathodic ray tube dismantling with a special focus on plastics was investigated. Only the tasks that need human skills were assigned to human operators while all other tasks were performed by robots. The study resulted in a more efficient material recovery than the previously manual processes, primarily in terms of raising the quantity of recovered materials and plastic, which means higher revenues with significant additional benefits regarding the work environment via keeping humans away from the most dangerous tasks. Other studies also emphasized the advantages of human-robot collaboration for recycling [49], assembly, and disassembly [50] processes in several areas of frameworks for manufacturing and remanufacturing while focusing on their usefulness to support CE. Better productivity and profitability are usually achieved by assigning dangerous tasks to robots with other tasks with value added allocated to humans.

2.2.6. Cyber-Physical Systems

CPSs were the least discussed I4.0 technology for boosting CE practices [4]. However, CPSs showed an obvious orientation to support the CE direction. Many researchers saw CPSs as an orientation to enhance the management of products' lifecycle or the development of new services, primarily for maintenance [51]. A few cases showed that the focus was on practices of remanufacturing and the management of multiple users' systems, for instance, in natural resource extraction [52]. Additionally, a cyber-physical system was introduced for waste management optimization that focused on sustainability and energy efficiency [53] that showed effective results in saving the used energy.

As a conclusion to this introduction and brief literature review, the following notes are considered:

- The literature stated various applications of the developed I4.0 technologies in the manufacturing areas with a high potential of raising the CE. It reflected a possibility of direct/indirect impact on the CE orientation.
- I4.0 technologies contribute directly to digitization, full product life analysis, dynamic feedback, and other tools that allow deeper and more inclusive analysis and optimization in the tackled system.
- Many studies focused on finding analysis tools that measure the sustainable impact of applying I4.0 technologies. However, most of these studies had a narrow domain and limited results because they tackled limited manufacturing areas. Additionally, analyzing this impact can be complex research easily due to the various I4.0 applications and compound data that cannot be attributed to specific reasons directly.
- A scientific gap in the correlation between I4.0 and its impact on CE does exist. While the correlation of this potential relationship attempted to be shown, validating the correlation is very limited.

Therefore, this research aims to assist in supporting the CE efficiency growth in manufacturing companies. This research focuses on reaching a better comprehension of how I4.0 technologies can properly support the possible active involvement of raising CE efficiency next to, maybe, validating this impact.

While the literature in Section 2.2 revealed various I4.0 technologies that can be applied in the manufacturing area, researching the real application of those technologies is considered a real challenge due to the needed time to adopt them in the companies. Mostly, this adoption requires a lot of time, effort, and training. After that, empirical research is needed to collect the data from these companies. From this perspective, one of the strongest pillars of this research is to have inclusive data that almost covered all the manufacturing companies in the tackled countries. It was collected within the EMS project that is coordinated by The Fraunhofer Institute for Systems and Innovation Research ISI [54]. The latest survey was carried out in eleven countries in 2018 (that is used in this research). It covered a core of indicators in the innovation fields. However, not all the mentioned I4.0 technologies in the literature were used in this project. Therefore, according to the data available in our sample, we will analyze only AM, robots, and simulation partially (since only product simulation technology is covered). The collected data of the I4.0 technologies in Section 2.2 can be a good reference for further investigations on the same topic as well. On the other hand, the literature in Section 2.1 included two aspects of CE, one showed CE as a promising approach toward sustainability and the other one showed the need to measure this potential impact because it is difficult to provide direct influence due to the various playing factors in practice. Within the mentioned survey used in this research, we worked on mapping related CE. Therefore, according to the data available in our sample, we will analyze the adopted technologies related to water recycling and reusing and kinetic and process energy recuperating in the manufacturing companies. While no direct conception was structured about whether there are patterns between applying such technologies and the size, products type, conducted R&D actions, sector or another specification of the companies [55], a common consciousness of such adoption's usefulness is widespread, especially regarding the energy saving [56]. Moreover, we considered other actions in the manufacturing companies that are connected to CE indirectly, as they reflect having made major improvements in the products or process and improved environmental impact. These actions will be considered under a separate category titled product characteristics.

3. Methodology and Data

In this chapter, the used methodology and data are to be explained.

3.1. Methodology

Within the tackled literature, various studies used different methods to reach their desired results. In a study about connecting CE and I4.0 [57], the cause-and-effect relationship was used between various dimensions of I4.0 and CE in the supply chain area. The dimensions of I4.0 were obtained through the analysis of exploratory factors. A total of 161 responses from Indian manufacturing companies were the sample data. Additionally, they performed a cause-and-effect relationship through DEMATEL analysis. Other studies also addressed different hypotheses to be analyzed in a specific way. In a study that examined the role of I4.0 on CE practices and the capability of the supply chain to increase the company's performance [58], eight hypotheses were presented while structural equation modeling was used for analyzing them. Additionally, in investigating how I4.0 technologies and stakeholder pressure influence circular product design and impact company performance [59], five hypotheses were assumed. Partial least squares path modeling for data analysis was used. In another study [60], a qualitative analysis of selected case studies aimed to answer three research questions. The results were visualized to highlight applying digital technologies' effects on processes, companies, products, and supply chain within the transition into CE. Likewise, in a study regarding adopting the I4.0 technologies pattern in manufacturing companies [2], four hypotheses were presented about using smart manufacturing technologies. It included data analysis of a questionnaire survey of companies, so relevant to our research. The first step to analyzing the data was by identifying the tackled companies into several maturity scales regarding their adoption level of smart manufacturing technologies. Two groups with distinct technological levels were needed at a minimum for testing the hypotheses and finding out different patterns between these groups in order to explain the I4.0 adoption. Then, a hierarchical cluster analysis was used to determine the adequate number of groups for sample division. After having obtained the cluster compositions, an analysis of the demographic aspect of the cluster members was performed. Pearson's Chi-squared test was used to reject the null hypothesis that stated that there is no association among the variables. Additionally, the test of Fisher's exact was used for associations to reach four observations or fewer.

As we could find, there is a wide spectrum of approaches and methods used in the literature to investigate I4.0's impact on CE. The rationale of our methodology is based on our research questions and available data. The general research question is whether there are relationships between the use of I4.0 and CE in manufacturing companies. The data comprise a sample of central European manufacturing companies, which includes the use of selected I4.0 and CE technologies. To find out if there are relationships, the raw data were filtered at the beginning to exclude any invalid entries, and then, we built our methodology in two steps. First step: grouping the data to see if there are some differences in the use of technologies in the subsample groups. For this, contingent tables were used. This helped to find out where to expect possible relations between technologies. In this step, we also included non-I4.0 technologies to see if there are differences between the use of I4.0 and non-I4.0 technologies. Second step: logistic regression (by IBM SPSS Statistics 25 software, Armonk, NY, USA) was used to validate the expected relations. Before starting the logistic regression, a correlation test was applied to the independent variables to affirm their independence. It should be mentioned that even in a case where logistic regression shows a statistically significant relation between I4.0 and CE technology, it does not reflect a causal relationship. Therefore, the odd ratio was used to reflect the strength of these possible relationships, but it cannot affirm them as a direct influence. In other words, with our methodology, we can only show relations, but not affirm if I4.0 supports or enhances the CE. This is one limitation of the used methodology. Nevertheless, showing the existence of the significant relationship can help other researchers to focus on this relationship and investigate causality.

3.2. Data and Hypotheses Building

3.2.1. Data

The tackled data are collected within the EMS project. The sample (N = 798) contains data collected in Lithuania [61], Slovakia [62], Austria [63], Croatia, and Slovenia [64] as part of a European manufacturing survey in 2018. The numbers of companies in Lithuania, Slovakia, Austria, Croatia, and Slovenia are, respectively, 199, 114, 253, 105, and 127. These five countries were chosen since they represent relatively similar numbers of manufacturing companies. Additionally, the sample size of each country separately is considered small for conducting statistical tests.

By analyzing the EMS data, the technologies that have a direct connection with our research were selected and stated in Figure 1. The mutually used questions within the EMS project in the mentioned five countries were considered since a few differences are considered between one country and another in the actual practice of the survey. Additionally, used abridgments for the tackled technologies are mentioned in Figure 1.

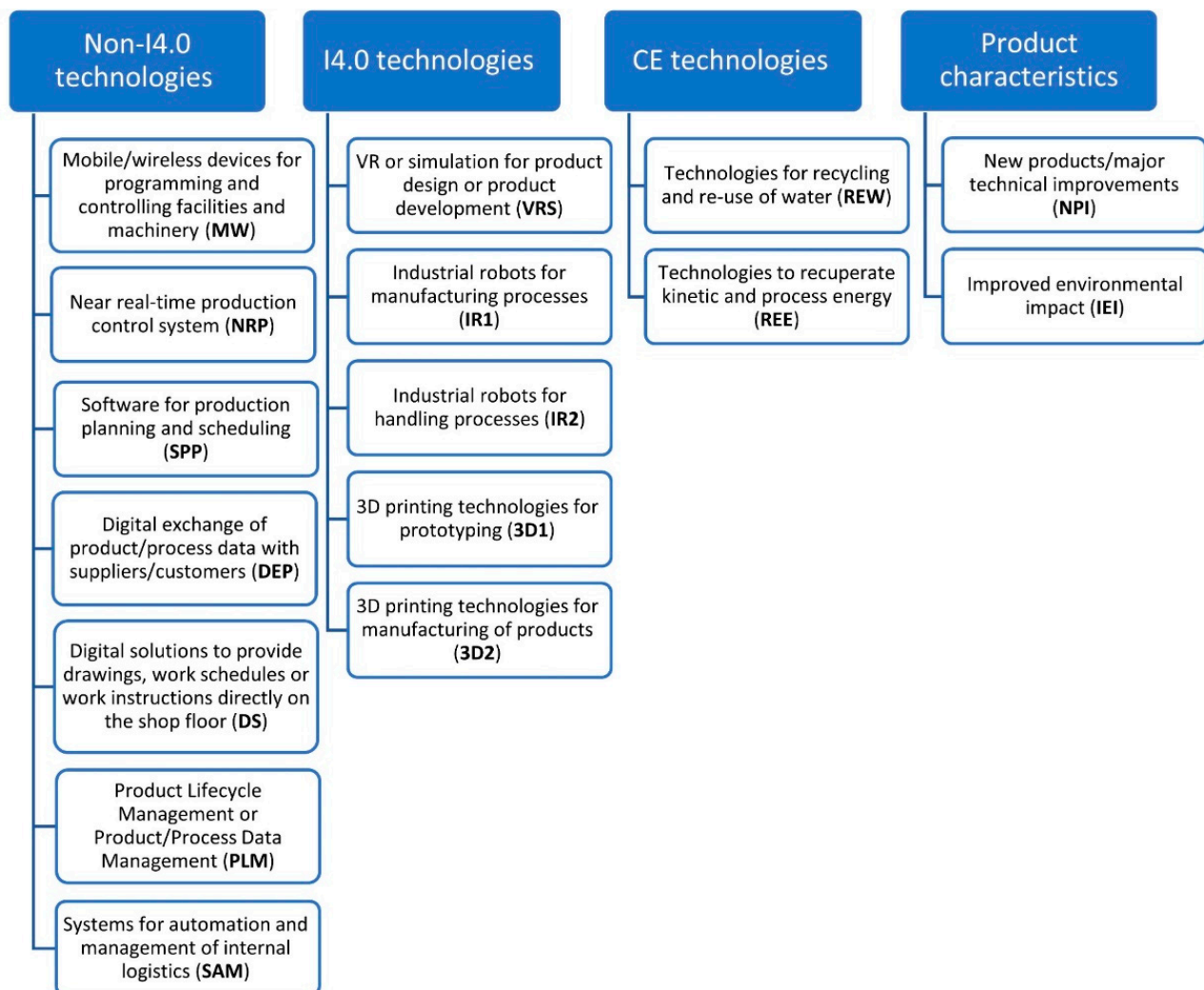


Figure 1. List of used technologies and product innovation (variables) with abridgments.

To be able to connect this survey's results with the aim of this research, we classified the related data into four categories. First, non-I4.0 technologies that provide solutions based on digital and automation, however, they are not modern and/or innovative to be considered as I4.0 technologies depending on the literature. Second, I4.0 technologies that are related to the literature in Section 2.2. Third, CE technologies that show taken actions

in the companies for water saving by reusing or recycling, or for energy recuperating. Fourth, product characteristics that can be connected to CE indirectly by showing major improvements or new products that reflect the research and development aspect of the company as well as improved environmental impact of a new or improved product, for instance, extended product life, improved recycling, or reduced environmental pollution.

3.2.2. Hypotheses Building

According to the available data and depending on the classified technologies (Figure 1), we built a research question, if there is a relationship (potentially effect) between the mentioned I4.0 + non-I4.0 technologies and adopting the mentioned CE technologies in manufacturing companies. Based on that, two hypotheses were developed:

Hypothesis 1a (H1a). *Implementation of CE technologies that support recycling and re-use of water is related to the adoption of I4.0 technologies.*

Hypothesis 1b (H1b). *Implementation of CE technologies that support recuperating process energy is related to the adoption of I4.0 technologies.*

The research model (Figure 2) is the same for testing the two hypotheses in two steps, with only a difference in the dependent variable. While in the validation of H1a, the dependent variable is “technologies for recycling re-use water”, in the case of H1b, it is “technologies to recuperate kinetic and process energy”. For the independent variables, we have used all technologies, which are included in the data sample, including I4.0 and non-I4.0 technologies (Figure 1).

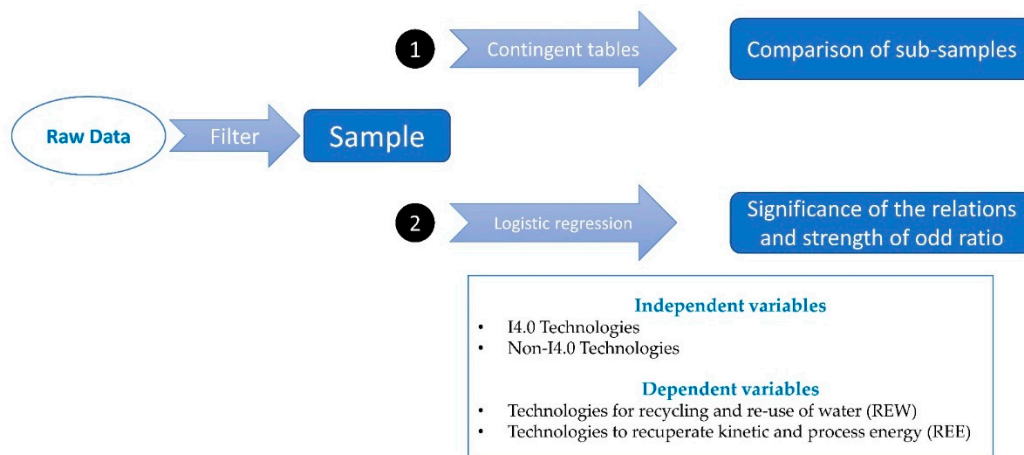


Figure 2. Research model 1 for testing H1a and H1b.

Since we have data related to the product characteristics that can be connected to CE indirectly (Figure 1) in our sample, we also built a second research question, if there is a relation (potentially effect) between the use of I4.0 + CE technologies and improved environmental impact of the product. Based on that, two additional hypotheses were developed:

Hypothesis 2a (H2a). *Introducing new products or major technical improvements is related to the implementation of I4.0 technologies.*

Hypothesis 2b (H2b). *The development of products that lead to an improved environmental impact is related to the implementation of I4.0 technologies.*

The research model (Figure 3) represents the same two steps methodology as above for testing both hypotheses, with changing the independent and the dependent variables. While in the validation of H2a the dependent variable is “introducing new products or major

technical improvements of products”, in the case of H2b it is “improved environmental impact of a new (or improved) product”. Even though H2a is not directly connected to CE, we used it to allow us to find out if the use of specific I4.0 technologies has a different relation to new product development and its improved environmental impact. In this model, as the independent variables, we have used all technologies in the data sample, including I4.0, non-I4.0, and CE technologies (Figure 1).

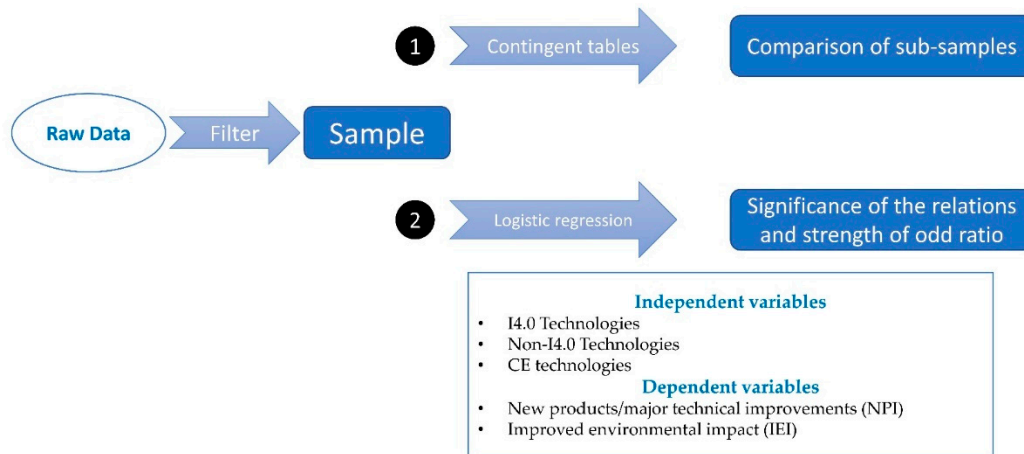


Figure 3. Research model 2 for testing H2a and H2b.

For analyzing the results, the significance was considered, which is referred to as ‘Sig’ where it should be equal to or less than 0.05/0.1 to consider them acceptable. The results that achieve this condition are highlighted with dark grey color for a significance less than 0.05 and with light grey color for a significance equal to or less than 0.1. After that, $\text{Exp}(B)$ was considered, which refers to the odd ratio that simply comes from B raised to the exponent. The odd ratio indicates no effect when its value is 1. When the odds ratio is greater than 1, it indicates that the specific predictor increases the odds of the output, while an odds ratio less than 1 indicates that the specific predictor decreases the odds of the outcome [65]. Therefore, Sig and $\text{Exp}(B)$ are to be used to discuss the results where the higher $\text{Exp}(B)$ means higher likelihood to have an impact on the dependent variable.

3.3. Results and Discussion

This section is divided into two sub-sections for presenting the results of the two research models, 1 and 2.

3.3.1. Relations between the Use of I4.0 and CE Technologies (Research Model 1)

Within this model, possible relations for the impact of used technologies in the areas of production control, digital factory, automation and robotics, and AM technologies on the adoption of REW (resp. REE) technologies were analyzed. The differences between the companies’ percentages that use I4.0 (but also non-I4.0) technologies in the whole sample compared to the subsample of companies that are using REW (resp. REE) technologies in the manufacturing companies are presented in Table 1 and Figure 4.

By comparing the percentages for the whole sample and subsample of companies that use REW, we can find the highest differences in the case of three technologies (industrial robots for handling processes, near real-time production control system, and software for production planning and scheduling). There are also another three technologies showing differences (industrial robots for manufacturing processes, the digital exchange of product/process data with suppliers/customers, and systems for automation and management of internal logistics). Based on this, we expect relationships between the use of these technologies and the use of REW.

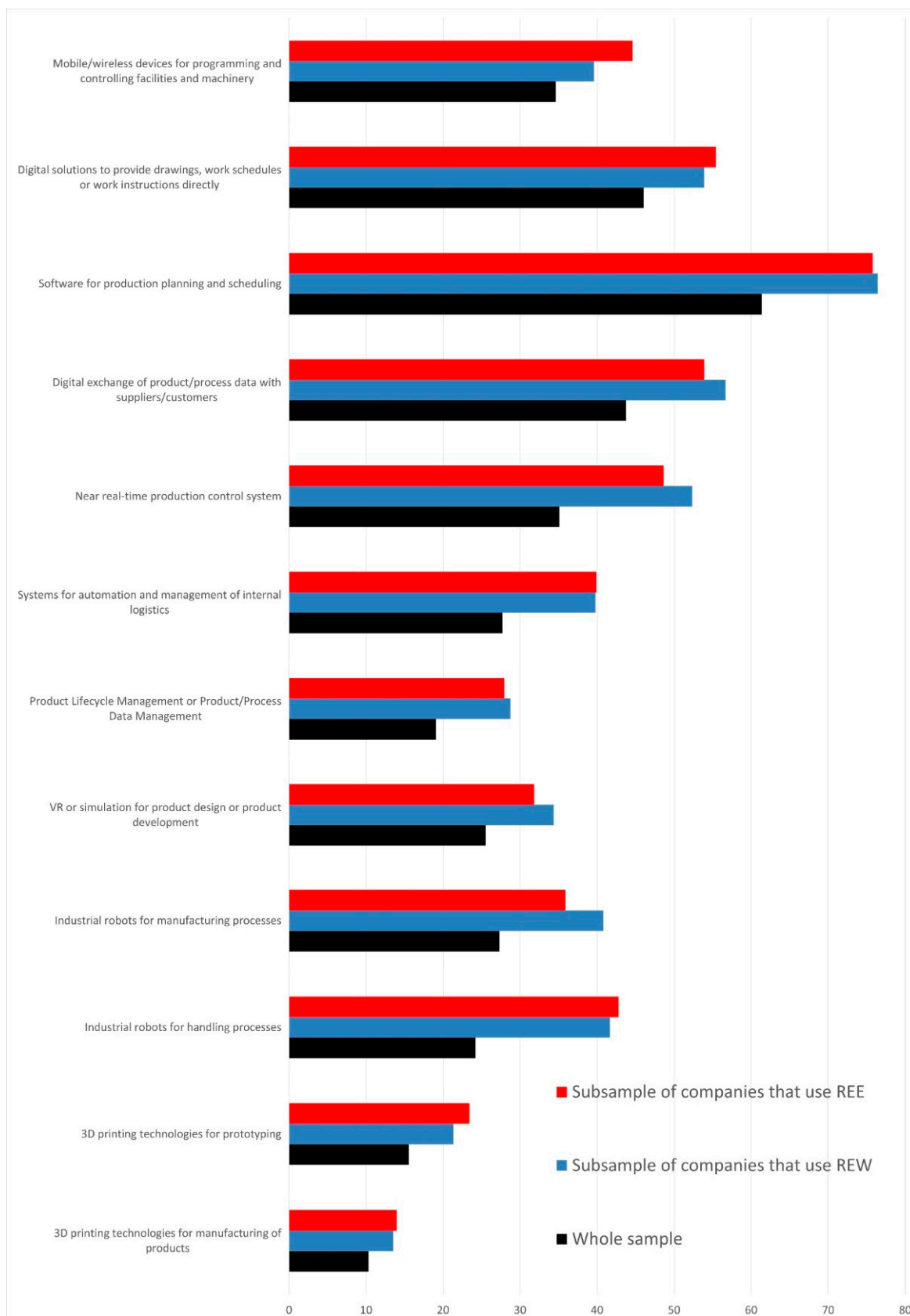


Figure 4. Comparison of companies’ percentages that use the I4.0 or non-I4.0 technology (specified on Y-axes).

Table 1. Comparison of companies' percentages that use the I4.0 or non-I4.0 technology (in row).

Technology	Whole Sample	Subsample of Companies That Use REW	Subsample of Companies That Use REE
MW	34.63	39.58	44.59
DS	46.04	53.93	55.41
SPP	61.39	76.44	75.78
DEP	43.76	56.68	53.92
NRP	35.07	52.36	48.65
SAM	27.72	39.79	39.91
PLM	19.07	28.75	27.957
VRS	25.52	34.375	31.82
IR1	27.34	40.84	35.87
IR2	24.22	41.67	42.79
3D1	15.56	21.35	23.42
3D2	10.33	13.54	13.96

By comparing the percentages for the whole sample and subsample of companies that use REE, we can find the highest differences also in the case of three technologies (industrial robots for handling processes, near real-time production control system, and software for production planning and scheduling). There are also another three technologies showing differences (systems for automation and management of internal logistics, the digital exchange of product/process data with suppliers/customers, and mobile/wireless devices for controlling facilities and machinery. Based on this, we expect relationships between the use of these technologies and the use of REE.

The statistical test is applied to validate the expected relationship and support or deny the hypothesis. The method for testing is the logistic regression by IBM SPSS Statistics 25 software. For the H1a test, the sample was $N = 543$ after filtering the raw data. Before testing, a correlation test was applied to the 12 independent variables (see Figure 1, I4.0, non-I4.0). The tackled variables (technologies) appeared to be independent where the highest correlation value was 0.3638 except for 3D1 and 3D2 technologies, which showed 0.533. These values allow us to consider the 12 technologies as independent variables. The results of the logistic regression are presented in Table 2.

Table 2. Results of logistic regression (research model 1, dependent variable—REW).

Technology	B	Std. Err.	Wald	df	Sig	Exp(B)	CI 95%	
							Lower	Upper
MW	−0.222	0.231	0.925	1	0.336	0.801	0.510	1.259
DS	0.076	0.229	0.109	1	0.742	1.079	0.688	1.691
SPP	0.463	0.266	3.029	1	0.082	1.588	0.943	2.674
DEP	0.342	0.222	2.373	1	0.123	1.407	0.911	2.174
NRP	0.667	0.236	7.992	1	0.005	1.949	1.227	3.096
SAM	0.151	0.237	0.405	1	0.525	1.163	0.731	1.849
PLM	0.059	0.281	0.044	1	0.834	1.061	0.612	1.839
VRS	0.192	0.252	0.581	1	0.446	1.212	0.739	1.988
IR1	0.466	0.235	3.928	1	0.047	1.594	1.005	2.527
IR2	0.711	0.233	9.336	1	0.002	2.035	1.290	3.210
3D1	−0.217	0.322	0.452	1	0.502	0.805	0.428	1.515
3D2	−0.190	0.366	0.270	1	0.603	0.827	0.403	1.695
Constant	−2.077	0.228	82.922	1	0.000	0.125		

As we can see in Table 2, four technologies of SPP, NRP, IR1, and IR2 showed statistically significant relationships with the dependent variable REW. IR2 and NRP showed the strongest significance of relationship and influence (Exp(B)) on the REW. Based on this, we can conclude that the significance of the relationship between the use of specific technology and the use of REW is not dominantly influenced by whether it is I4.0 technology or not.

To validate the expected relationship in H1b, we used the logistics regression test again. Before this analysis, we filtered the raw data accordingly (final N = 546 companies). The correlation test is the same as the previous one (same 12 technologies). The results of the logistic regression test are presented in Table 3.

Table 3. Results of logistic regression (research model 1, dependent variable—REE).

Technology	B	Std. Err.	Wald	df	Sig	Exp(B)	CI 95%	
							Lower	Upper
MW	0.205	0.216	0.897	1	0.344	1.227	0.803	1.875
DS	0.196	0.220	0.800	1	0.371	1.217	0.791	1.872
SPP	0.631	0.254	6.152	1	0.013	1.879	1.142	3.094
DEP	0.078	0.214	0.133	1	0.715	1.081	0.710	1.646
NRP	0.370	0.229	2.614	1	0.106	1.448	0.925	2.266
SAM	0.389	0.226	2.952	1	0.086	1.475	0.947	2.298
PLM	0.011	0.271	0.002	1	0.969	1.011	0.594	1.720
VRS	0.018	0.246	0.005	1	0.942	1.018	0.629	1.647
IR1	0.006	0.232	0.001	1	0.978	1.006	0.639	1.585
IR2	0.973	0.226	18.447	1	0.000	2.645	1.697	4.124
3D1	0.041	0.307	0.018	1	0.893	1.042	0.571	1.902
3D2	−0.384	0.355	1.171	1	0.279	0.681	0.340	1.875
Constant	−1.940	0.221	77.411	1	0.000	0.144		

As we can see in Table 3, four technologies of SPP, NRP, SAM, and IR2 showed statistically significant relationships with the dependent variable REE. IR2 and SPP showed the strongest significance of relationship and influence (Exp(B)) on the REE. We can conclude also in the case of REE (similarly to REW) that the significance of the relationship between the use of specific technology and the use of REE is not dominantly influenced by whether it is I4.0 technology or not. It is important to highlight that NRP showed a 0.106 significance result in Table 3. It is even more than the significant step of 0.1, it is very close to it, therefore, it was considered equal to 0.1.

3.3.2. Relations between Use of I4.0, Non-I4.0, CE Technologies, and Product Characteristics (Research Model 2)

Within this model, possible relations for the impact of used technologies in the areas of production control, digital factory, automation and robotics, and additive manufacturing technologies on the new or improved product development (NPI), (resp. improved environmental impact (IEI) of the product) were analyzed. The differences between the companies' percentages that use I4.0, non-I4.0, and CE technologies in the whole sample compared to the subsample of companies that have performed NPI, (resp. IEI) are presented in Table 4 and Figure 5.

By comparing the percentages for the whole sample and subsample of companies that have performed NPI, we can find that the highest differences are in the case of three technologies (NRP, MW, and VRS). Other technologies showed less significant differences, but interestingly, some were negative (the highest negative difference was SPP), but as value it was small. Based on this, we expect a relationship between the use of these technologies and the execution of NPI.

By comparing percentages for the whole sample and subsample of companies that have carried out IEI, we can find the highest differences in the case of five technologies (DS, SPP, PLM, VRS, and IR2). Additionally, two other technologies (IR1 and 3D1) showed moderate differences. Based on this, we expect more relationships between the use of these technologies and the execution of IEI.

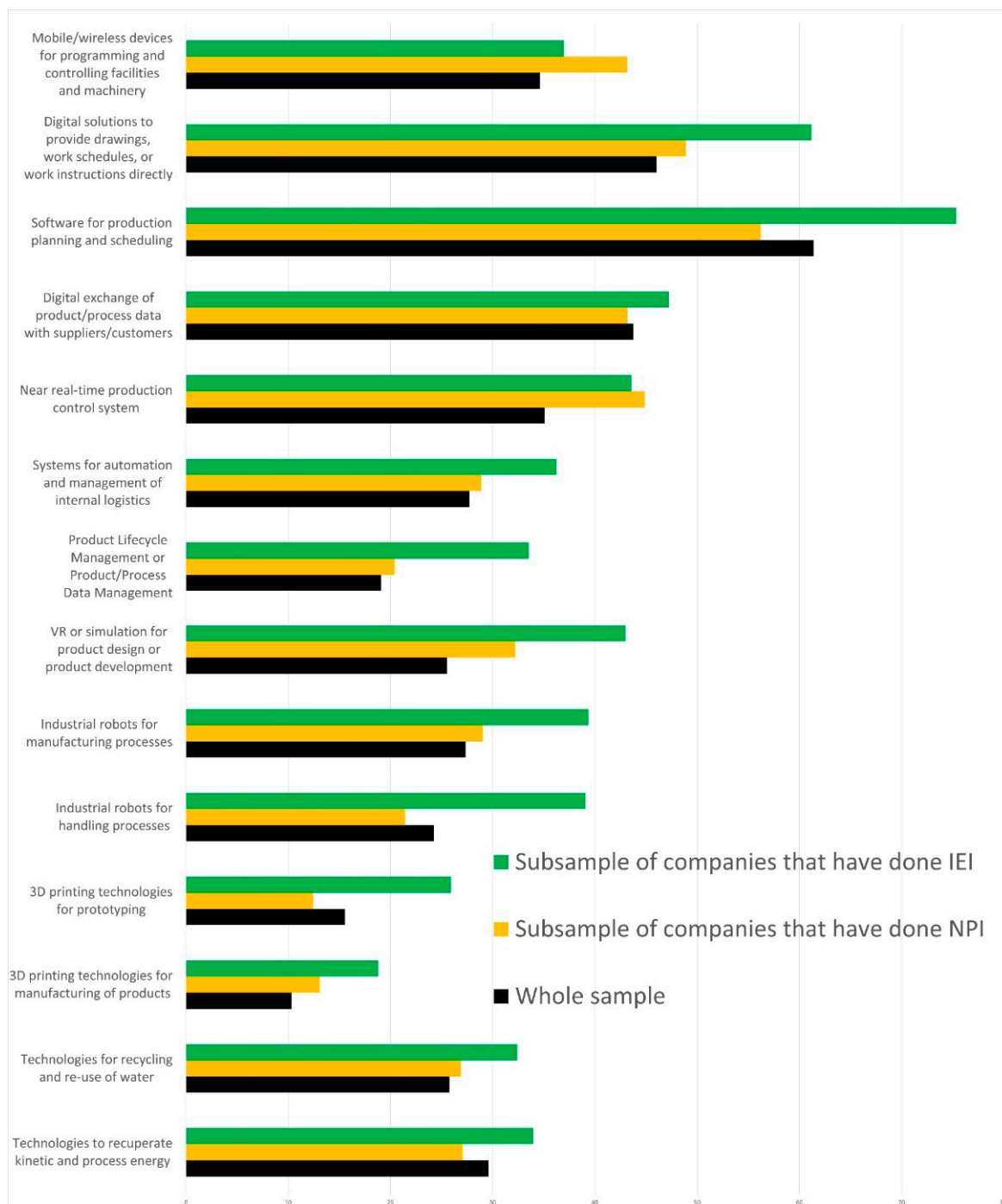


Figure 5. Comparison of companies’ percentages that use the I4.0, non-I4.0, or CE technology (specified on Y-axes).

Table 4. Comparison of companies’ percentages that use the I4.0 or non-I4.0 technology (in row).

Technology	Whole Sample	Subsample of Companies That Have Done NPI	Subsample of Companies That Have Done IEI
MW	34.63	43.17	36.99
DS	46.04	48.89	61.19
SPP	61.39	56.22	75.34
DEP	43.76	43.18	47.22
NRP	35.07	44.89	43.58

Table 4. Cont.

Technology	Whole Sample	Subsample of Companies That Have Done NPI	Subsample of Companies That Have Done IEI
SAM	27.72	28.89	36.24
PLM	19.07	20.41	33.52
VRS	25.52	32.20	42.99
IR1	27.34	29.03	39.37
IR2	24.23	21.43	39.09
3D1	15.56	12.43	25.91
3D2	10.33	13.07	18.81
REW	25.77	26.9	32.39
REE	29.59	27.06	33.95

To validate the expected relationship in H2a, we used the logistics regression test again. Before this analysis, we filtered the raw data accordingly (final N = 535 companies) and made the correlation test for 14 technologies (12 technologies + 2 CE technologies) (see research model 2 and Figure 1). The highest correlation value for the two new variables (technologies) was 0.346, which is still low and allows us to consider the 14 technologies as independent variables. The results of the logistic regression are presented in Table 5.

Table 5. Results of logistic regression (research model 2, dependent variable—NPI).

Technology	B	Std. Err.	Wald	df	Sig	Exp(B)	CI 95%	
							Lower	Upper
MW	−0.096	0.227	0.179	1	0.672	0.908	0.583	1.417
DS	0.143	0.214	0.447	1	0.504	1.154	0.759	1.755
SPP	−0.187	0.228	0.676	1	0.411	0.829	0.531	1.296
DEP	0.140	0.210	0.444	1	0.505	1.150	0.763	1.734
NRP	0.272	0.239	1.293	1	0.255	1.312	0.821	2.097
SAM	0.175	0.247	0.499	1	0.480	1.191	0.733	1.934
PLM	0.420	0.316	1.764	1	0.184	1.522	0.819	2.830
VRS	0.825	0.273	9.105	1	0.003	2.281	1.335	3.898
IR1	0.069	0.235	0.086	1	0.769	1.071	0.676	1.698
IR2	0.270	0.244	1.222	1	0.269	1.310	0.812	2.113
3D1	0.748	0.361	4.298	1	0.038	2.113	1.042	4.286
3D2	0.427	0.417	1.048	1	0.306	1.533	0.677	3.472
REW	0.196	0.236	0.686	1	0.408	1.216	0.765	1.932
REE	−0.168	0.226	0.550	1	0.458	0.845	0.542	1.318
Constant	0.013	0.176	0.005	1	0.942	1.013		

As we can see in Table 5, only the two technologies of VRS and 3D1 showed statistically significant relationships with the dependent variable—NPI. They both showed strong significance of relationship and influence (Exp(B)). Based on this, we can conclude that surprisingly, the significant relationships are not between technologies that we expect according to the differences identified above (Figure 5), but the main finding is that it seems that I4.0 technologies dominate over non-I4.0 and CE technologies in having significant relationships with the execution of NPI in manufacturing companies.

In the last part of the analysis, to validate the expected relationship in H2b, we used the logistics regression test again. Before the analysis, the raw data were filtered accordingly (final N = 430 companies). The correlation test is the same as the previous one (same 14 technologies). The results of the logistic regression are presented in Table 6.

Table 6. Results of logistic regression (research model 2, dependent variable—IEI).

Technology	B	Std. Err.	Wald	df	Sig.	Exp(B)	CI 95%	
							Lower	Upper
MW	−0.190	0.247	0.592	1	0.441	0.827	0.510	1.342
DS	0.345	0.241	2.045	1	0.153	1.412	0.880	2.266
SPP	0.454	0.266	2.897	1	0.089	1.574	0.934	2.653
DEP	−0.383	0.241	2.538	1	0.111	0.682	0.425	1.092
NRP	−0.270	0.262	1.064	1	0.302	0.763	0.457	1.275
SAM	−0.018	0.259	0.005	1	0.944	0.982	0.591	1.631
PLM	0.949	0.300	10.001	1	0.002	2.583	1.434	4.651
VRS	0.620	0.255	5.916	1	0.015	1.858	1.128	3.061
IR1	0.167	0.244	0.468	1	0.494	1.181	0.733	1.904
IR2	0.573	0.256	5.014	1	0.025	1.773	1.074	2.927
3D1	0.078	0.325	0.057	1	0.811	1.081	0.572	2.042
3D2	0.481	0.375	1.643	1	0.200	1.618	0.775	3.375
REW	0.071	0.256	0.077	1	0.782	1.074	0.650	1.773
REE	0.139	0.251	0.307	1	0.580	1.149	0.702	1.880
Constant	−1.244	0.213	34.072	1	0.000	0.288		

As we can see in Table 6, four technologies of SPP, PLM, VRS, and IR2 show statistically significant relationships with the dependent variable—IEI. The strongest significance of relationship and influence (Exp(B)) on the IEI has PLM. Interestingly, despite the expected higher number of technologies to be related to the execution of IEI, the regression does not prove it. Nevertheless, in contrast to the execution of NPI, it seems that the significance of the relationship between the use of specific technology and the execution of IEI is not dominantly influenced by whether it is I4.0 technology or not.

3.4. Discussion of the Results

The investigation of the relations between the use of I4.0 and CE technologies (research model 1) showed that in general, it seems that both I4.0 technologies and non-I4.0 technologies could have significant relations with CE technologies (in our study REW and REE). Interestingly, both have significant relation with three identical technologies (IR2, NRP, and SPP) and one different for each. The most significant relation (measured by Sig. and Exp(B)) (Tables 3 and 4) in the case of both CE technologies is IR2, i.e., industrial robots for handling processes. This relation could be possibly connected to the technological level of the company. The existence of the relation with the second identical technology (NRP), for both CE technologies (especially the REW) could be caused by specific characteristics of the production process. The third commonly related technology (SPP) (especially significant for REE) can support previous arguments, that the company that uses REW or REE should be on some technological level and have a specific production process, where it can apply SPP. In the case of REW, there is one different significant technology (IR1). Explanation of significant relation with IR1 in the case of REW can lead us to the sectors such as automotive, electronics, etc., where the use of IR1 is widespread, so again to some specifics of the production process. In the case of REE, the different technology is SAM. We can only assume that some specifics of production process can take a role in this relation.

The results show significant relations of CE technologies (REW and REE) with robotics (IR1 and IR2), which is in partial agreement with e.g., the review of [7], who stated that there is most evidence of the positive impact of additive manufacturing and robotics on circularity in companies. This found relation (in the case of IR2) is also in accordance with Álvarez-de-los-Mozos et al. [48] and Renteria et al. [49]. However, another study [4] stated that additive manufacturing could be exploited to improve energy consumption, which is not in line with our results. Another finding [7] that showed AM and VRS having the potential to reduce energy consumption is also not supported by our results. In addition, they showed for robotics that CE energy indicators vary in a range between 1.7 and 2.7

(on Likert-scale 0–4), i.e., the value of the influence is medium-high, however, the impact on the CE water variable has been less valued than 1.7. Our results indicate the opposite situation since in our case REE has a significant relation with only one robotics variable (IR2) and REW has a significant relationship with both robotics variables (IR1, IR2), but we should be aware of the different methodologies and variables in both studies. Nevertheless, our results are in line with additional findings of [7] that identified small energy reductions (less than 5%) in relation to the use of robots, despite the energy consumption of the robots. When looking solely at the REE technologies, a significant relationship is found with SPP and SAM, in accordance with Rosa et al. [4], Bloomfield et al. [5], Lahrour et al. [28], and Leino et al. [29] and in case of NRP with Rosa et al. [4] and Hatzivasilis et al. [33]. When looking separately at REW technologies, significant relation was found with NRP that is in line with Rosa et al. [4] and Hatzivasilis et al. [33], and in the case of SPP with Rosa et al. [4], Bloomfield et al. [5], and Nascimento et al. [30].

The investigation of the relation between I4.0, non-I4.0, and CE technologies and execution of new or improved product development (NPI) (resp. new or improved products with improved environmental impact (IEI)) (research model 2) showed major differences. In the case of NPI as dependent variable, two technologies (VRS and 3D1) showed statistically significant relationships. Here, the explanation is quite clear since both VRS and 3D1 are logically tight to the product development. Moreover, this result confirms the validity of our data and analyses. Lastly, it should be mentioned that clear dominance of I4.0 technologies appears here. In the case of IEI as a dependent variable, the situation is different. Similar to NPI, VRS (as a product development tool) created significant relations with IEI. Nevertheless, even higher significance (also influence (Exp(B)) is in the PLM (Product lifecycle management or product/process data management). These are important findings, that PLM has the potential to be an influential factor in the improvement of the environmental impact of the products. There were also another two technologies (SPP and IR2) that showed statistically significant relationships with IEI. This is not so straightforward to explain, but we assume similarly to above, that it can be connected to the technological level of the company and specifics of the production process. Lastly, it should be mentioned that no clear dominance of I4.0 technologies over non-I4.0 was found. In addition, it seems that there was not a clear connection between the use of CE technologies and the development of a product with improved environmental impact.

Our results in the case of NPI (as a dependent variable) support the literature findings [2], which showed that there is a connection between the adoption of Smart Manufacturing and Smart Product technologies. Our finding on VRS relation to product development was also in accordance with Rosa et al. [4], Kuik et al. [36], and Wang et al. [37]). Another study [4] showed that I4.0 technologies can have a positive effect on the lifecycle management of products, while we found similarly that the use of virtual reality and robotics is related to the development of the IEI (improved environmental impact of a new product) by the company. The results [7] that show robotics to have a medium influence (1.5–2.2 on Likert-scale 0–4) on reuse, and recovery characteristics of the products are also in agreement with ours since we identified the relationship between the use of robots (IR2) and IEI. Moreover, the relationship between IEI of the product and VRS technology is in line with the findings of Kuik et al. [36] and Wang et al. [37], while the relation with IR2 is in accordance with Álvarez-de-los-Mozos et al. [48] and Daneshmand et al. [50]. Finally, a relationship was found between IEI with PLM and SPP is also supportive of previous studies (Rosa et al. [4] and Unruh [27]).

The results of our analysis, from the view of tackled I4.0 and non-I4.0 technologies, showed a statistically significant relationship with dependent variables (REW, REE, NPI, IEI) in a few of them. Interestingly there were only two technologies (SPP and IR2) that showed a significant relationship (so potential impact) on the CE technologies (REW, REE) but also on the development of the product with improved environmental impact (IEI). What is behind this wider “pro-environmental” scope of these two technologies (in comparison to others) is not clear but could guide the focus of future research in this field.

Regarding the validity and limitations of this study, three issues should be considered. First, the used data were collected from the manufacturing companies only, which excludes other areas where applied I4.0 technologies can have an impact on CE such as service, health, transportation, and education sectors. Second, despite the questions used in the survey were formed in a few steps and pre-tested, invalid answers or human mistakes can happen. Third, the data were collected in 2018. While only four years were passed on this survey, fast development in this topic is expected.

4. Conclusions

Our results show that eight of the tackled twelve (resp. fourteen) technologies have a significant relation with CE technologies (research model 1) or CE improvements of products (research model 2).

Regarding CE technologies (in our study REW and REE), the investigation of their relations with the use of I4.0 technologies showed that, in general, it seems that both I4.0 technologies and non-I4.0 technologies could have significant relations with them, so they could be potentially influenced or enhanced by both. Interestingly, both CE technologies have significant relation with three identical technologies (IR2, NRP, and SPP) and one different for each, while in both cases the most significant is IR2. The explanation of findings directs us to the characteristics like the technological level of the company or specifics of the production process. Our findings support previous studies that showed a positive impact of robotics on circularity in companies but are not in line with studies that showed additive manufacturing or virtual reality could be exploited to improve energy consumption.

Regarding CE improvements of products (in our study improved environmental impact (IEI) of new or improved products), the investigation of its relations with the use of I4.0 technologies showed no clear dominance of I4.0 technologies over non-I4.0. It was found that VRS as I4.0 (resp. product development) technology relates significantly, but also non-I4.0 (PLM technology) has even higher significance. We consider this identified relation an important finding because it reveals the PLM's potential to be an influential factor in the improvement of the environmental impact of the products. Significant relation with the other two technologies SPP and IR2 is not so straightforward to explain, but we assume that the technological level of the company and specifics of the production process could lie behind it. Regarding the relationship with CE technologies, it seems that there is no connection between product development with IEI and these technologies. Our findings are not in contradiction with previous studies, for example, that I4.0 technologies can have a positive effect on the lifecycle management of products or that robotics has a medium influence on the reuse and recovery characteristics of the products.

On the other hand, four of the twelve (resp. fourteen) tackled technologies did not show any significant relation with CE technologies (research model 1) or CE improvements of products (research model 2) that are, namely, MW, DS, DEP, and 3D2.

Our results, from the view of tackled I4.0 and non-I4.0 technologies, show that there are only two technologies (SPP and IR2) that have a significant relationship (therefore potential impact) on the CE technologies (REW, REE) but also on the development of the product with improved environmental impact (IEI). This wider CE relationship can guide the focus of future research in this field.

This research confirms the potential CE efficiency growth in manufacturing companies by adopting the I4.0 technologies. While not all the technologies showed significant relations, the achieved results still give strong affirmation in accordance with the literature review in the direction of that various application of the developed I4.0 technologies have a high potential of raising the CE. This research gains special importance since it is based on a large sample of companies (N = 798) and handled numerous technologies, but it has some limitations regarding its focus on Central Europe and the manufacturing industry.

Author Contributions: Conceptualization, M.Z.A. and J.Š.; methodology, M.Z.A. and J.Š.; software, M.Z.A.; formal analysis, M.Z.A. and J.Š.; data curation, J.Š.; writing—original draft preparation, M.Z.A. and J.Š.; writing—review and editing, M.Z.A., J.Š. and T.B.; visualization, M.Z.A.; supervision, J.Š. and T.B.; funding acquisition, T.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: This work is supported by the ÚNKP-22-3 new national excellence program of the ministry for innovation and technology from the source of the national research, development and innovation fund. This work is also supported by KEGA research grant 019TUKE-4/2022 Preparation of managers of new production structures of the future on the principles of Overall Equipment Effectiveness (OEE) through the education of students in the subject of Production Management in the study program of Industrial Engineering.

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

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