Theses of doctoral (PhD) dissertation

ANALYSIS OF THE RELATIONSHIP BETWEEN DIGITALIZATION AND MANUFACTURING COMANIES' BUSINESS PERFORMANCE IN THE LIGHT OF SUSTAINABLE DEVELOPMENT

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Debrecen, 2021

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1. RESEARCH BACKGROUND

Nowadays, it has resulted in the importance of logistics and process approach, the growth and rapid change of consumer demands, acceptable quality, flexibility and speed. It has become important for companies not only to react to events afterwards, but also to meet customer needs, to act proactively and proactively in the economic market. Recent developments have increased research and development costs, company size, use of IT systems, and customer demand for company flexibility.

The role of production has become strategically important in this competition. Ensuring the product quality required by customers can only be achieved by developing the right logistics processes and manufacturing technologies. The role of production optimization and efficiency in the supply chain is constantly growing, as a significant part of the company's costs are generated here.

The primary goal of the dissertation is to examine how the emergence of new technologies, the use of corporate governance systems and IT tools affect the business performance of companies. How do the supporting and hindering factors of strategic goals, developments and investments affect the innovation activity of companies.

Continuous improvement in both logistics and manufacturing has become essential for companies to maintain or increase their competitive advantage. A necessary condition for competitiveness, and one of the possible ways to increase it, is to create a fully comprehensive, centralized, easy-to-understand IT background for corporate operations.

One of the biggest positives of the introduction of Industry 4.0 is that production processes are optimized along the entire length of the value chain. Instead of the production cells that are still isolated today, fully integrated and automated production lines will be created. Productivity, flexibility, quality and speed of manufacturing processes are increasing. The Industry 4.0 initiative is still in its infancy in Hungary, but the positive thing is that the potential of the digitalisation of Hungarian industry is huge.

By innovation in technological processes we mean the application of new or significantly renewed production methods. It is important to put in place systems that can significantly increase the efficiency of the delivery and production of existing products. Innovation is most hampered by risk-taking, which, in addition to costs, is mainly due to the increasing difficulty of gaining customer acceptance and a lack of market information. In my research, I pay attention to the analysis of both external and internal risks, I examine what risk factors food companies may face as a result of technological change.

The economic, social and ecological impact of technologies on food companies can be identified as an unexplored field of research, so I consider it important to research the topic in Hungarian food companies where I know the novel technologies used in production and their economic, social and ecological impact. to examine.

The activity of publications in recent years shows that innovation will continue to be a central issue in the production of companies, and various publications and debates will contribute to the further development of innovative theoretical and practical technologies. In my dissertation, I elaborate on the relationship between Industry 4.0 technologies and business performance, and analyze what variables influence these two factors.

2. RESEARCH OBJECTIVES AND INTRODUCTION OF RESEARCH HYPOTHESES

In recent years, the Industry 4.0 concept has become increasingly popular as one of the most important tools for companies to improve performance and provide answers to the challenges of the recent revolution, primarily through the complete digitalisation of industrial processes. Europe, including Hungary, needs Industry 4.0 to maintain or possibly improve its competitiveness. In Hungary, mainly multinational companies have enough expertise and capital to be able to use the IV. opportunities provided by the Industrial Revolution.

In the course of technological developments, it is extremely important to examine which areas the companies want to develop in the long run. However, it is not negligible what supportive and disincentive factors may help or hinder Industry 4.0 developments today, as well as what risk factors should be considered when purchasing a new device.

Sustainable Industry 4.0 can be identified as an as yet unexplored area of research for food companies. I consider the research of the topic in Hungarian food production companies to be especially important, where I can specifically study the novel technologies used in production and their economic, social and ecological impact.

New technologies also carry risk factors that influence the decisions of business leaders. In my dissertation, I pay attention to the analysis of both external and internal risks, examining what risk factors food companies may face as a result of technological change.

The overall objective of my dissertation is to assess the strategies, developments and new technologies of Hungarian food production companies, which can have an impact on the business performance of companies, changes in risk factors and economic, social and ecological factors, ie sustainability.

In order to achieve this, I formulated the following sub-objectives:

1. Clustering of food companies based on innovation, sustainability and risk factors, and exploring the relationships between clusters and individual variables.
2. To examine the strategic goals of Hungarian food production companies and how they influence investments. Industry 4.0 is the main obstacle and support factor for developments and investments.

3. Provide an overview of the impact of sustainability factors (economic, social, ecological) on the use of new tools and business performance.
4. To explore the extent to which risk factors affect food companies ’investments in innovation tools.
5. To determine how the emergence of new technologies, the use of corporate governance systems and IT tools affect the processes and business performance of companies. Determining the factors of business performance and regression equations of relationships, setting up a path model.

I have previously formulated the following hypotheses:

H1: The vast majority of companies in the innovative food production cluster have more than 5 years of business experience.

H2: The more time a food company has been in business, the more it pays attention to sustainability factors.

H3: The extent of Industry 4.0 developments is negatively affected by high technology costs, lack of own resources and lack of skilled labor.

H4: The emergence of new tools and their use has a strong, positive, significant impact on the business performance of food companies.

H5: Among the risk factors, it is primarily the hidden costs and the risk of technological failures that deter food companies from new technological innovations.

H6: Of the sustainability factors, ecological factors have the most significant impact on business performance.

I believe that the results of the analysis can significantly enrich the previous research knowledge and the preparedness of the Hungarian food production companies for the current strategic challenges.

3. DESCRIPTION OF DATABASE AND APPLIED METHODS

3.1. Introduction of research work and demarcating the scope of research

In the course of the literature research, the collection of secondary information was mainly done by processing international and partly domestic literature. The predominance of the international literature is due to the fact that a small number of literature on the use and economic effects of Industry 4.0 technologies has been published in the Hungarian literature, and the related research only deals with certain sub-areas of the topic.

The first step in the primary data collection is the preparation of a questionnaire for Hungarian food industry companies. The questionnaire survey was typically conducted at online professional events between 2019 and 2020, as well as by personal and telephone inquiries, during which I received confirmation that the presentation of the topic in Hungary also plays an important role in the practical life of companies.

The professional basis for the preparation of the questionnaire is provided entirely by the literature research. I built the composition and structure of the questions and the possible answers on the basis of the literature read and collected during the research, as well as on the basis of preliminary consultations with 5 managers in the food industry, so I managed to draw attention to less examined factors. Thanks to this, I assessed the strategic goals of the companies, the factors hindering and supporting the developments, the willingness to use Industry 4.0 tools, the economic, social and ecological factors of sustainability, the risks of Industry 4.0, and the expected business performance and efficiency of the companies. The main consideration in selecting the research topics was to examine and analyze the Industry 4.0 tools and their effects along the factors listed.

During the questionnaire survey, I tried to get the opinion and data of the Hungarian food industry companies. Within the food industry companies (TEÁOR 10) I dealt with the following areas:

- Meat processing, preservation, production of meat products (TEÁOR: 101)
- Fish processing, preservation (TEÁOR: 102)
- Fruit and vegetable processing and preservation (TEÁOR: 103)
- Production of vegetable and animal oils (TEÁOR: 104)

- Milk processing (TEÁOR: 105)
- Manufacture of mill products and starches (TEÁOR: 106)
- Manufacture of bakery and farinaceous products (TEÁOR: 107)
- Manufacture of other food products (TEÁOR: 108)
- Production of fodder (TEÁOR: 109)

The structure of the questionnaire, its individual topics and the relationships between the topics are illustrated in *Figure 1*, which is also the initial model of PLS path analysis.

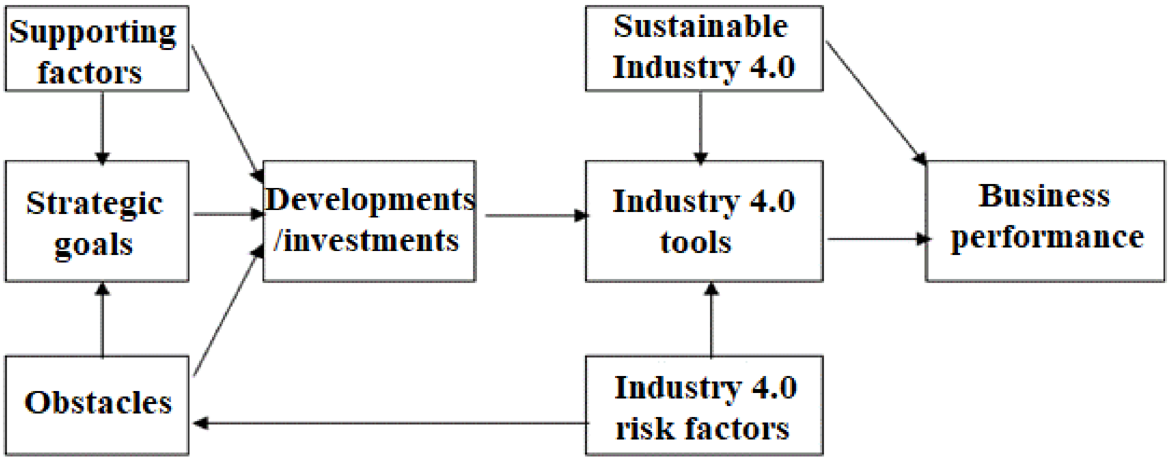


Figure 1: Theoretical framework of the questionnaire and initial model of PLS path analysis

Source: Own editing, 2021.

There are only 1157 companies in Hungary, which belong to the TEÁOR 10, food production company group, and these companies are scattered in Hungary. In order to have a sufficient amount of data for the analyzes, I considered it technologically important not to deal specifically with just one food production area, but with a larger group of food production companies.

Following the survey, I had 276 completed questionnaires at my disposal, which was reduced to 259 during data cleansing. I assigned statements to the 8 main topics of the questionnaire (barriers, supporting factors, strategic goals, developments, use of Industry 4.0 tools, sustainable Industry 4.0, risk factors, business performance), the consistency of which was established by a reliability test. I had to take 4 of the 123 statements made out of the model because the Cronbach’s alpha value was too low, thus reducing the alpha value of the entire area (*Table 1*). The remaining values have a relatively high Cronbach’s alpha value, suggesting the reliability of the internal consistency of the scales. In my research, the Cronbach's alpha values of the examined factors are above 0.7 in all cases, so their reliability based on internal consistency is adequate for further research.

Table 1: Statistical reliability of each dimension of food manufacturing enterprises

Areas examined	Subareas examined	Total number of claims	Number of statement taken out	Cronbach's alpha value
Strategic goals		10	0	,804
Supporting factors		8	1	,773
Obstacles		12	1	,876
Developments/ investments		7	0	,985
Industry 4.0 tools		10	0	,841
Sustainable Industry 4.0	Economic	8	0	,786
	Social	9	1	,804
	Ecological	9	1	,928
Industry 4.0 risk factors	Financial	6	0	,842
	Technological	5	0	,796
	Operating	4	0	,772
	Economic	4	0	,765
	Personnel	7	0	,833
	Legal	4	0	,799
	Environmental	3	0	,790
	Market	5	0	,786
	Business	4	0	,793
Business performance	Profitability	4	0	,789
	Growth	4	0	,820
Total		**123**	**4**	

Source: Own editing, 2021.

3.2. Methods used in the research

I consider the complex approach to be important, therefore it is justified to explore the connections as accurately as possible. I used statistical methods to process the collected data. The main methods used in my dissertation and the process of my research are shown in *Figure 2*.

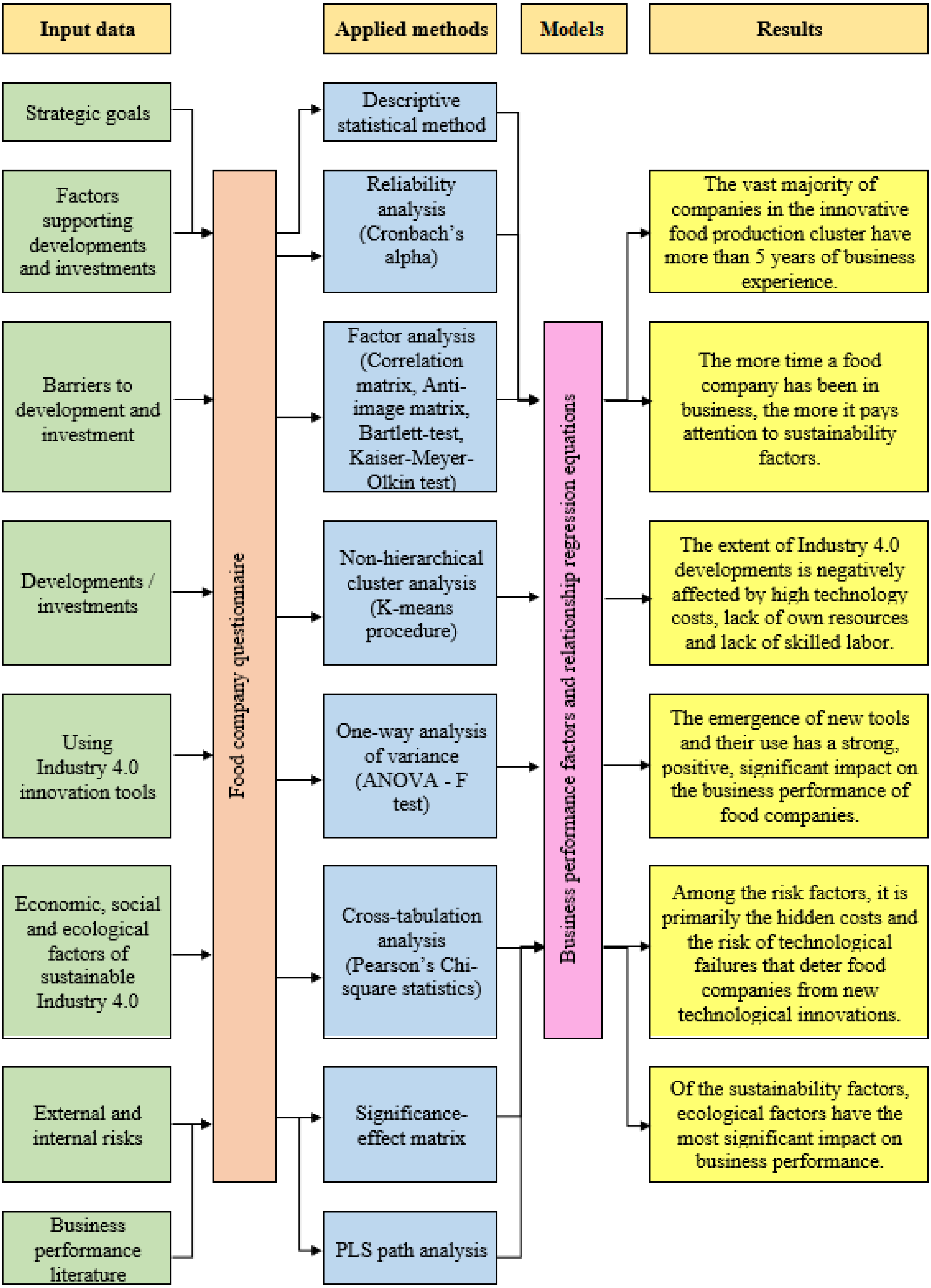


Figure 2: Summary diagram of the applied methods

Source: Own editing, 2021.

I started the data collection with a **pilot** survey, during which I received 45 responses from the respondents, 5 of them from companies that I could contact in person and online through my contacts. Based on the responses collected during the pilot research, the comments received by e-mail, and the lessons learned, I finalized the complete questionnaire. The responses obtained during the pilot research were not used for the analyzes.

To determine the internal consistency of the questionnaire, I perform reliability tests. **Cronbach's alpha** is currently the most accepted measure of internal consistency (CRONBACH, 1990). The Cronbach's alpha coefficient is basically a reliability indicator that can be calculated for summary scales, which can be a number between 0 and 1. Its value is considered acceptable between 0.70 and 0.85, as the scale below it is not consistent enough, and above it it may already contain a redundant, ie unnecessary surplus.

In my dissertation, I also used **cross-tabulation analysis**, which examines the relationship between two or more variables and their combined frequency distribution (MALHOTRA, 2009). A frequently used hypothesis testing method for nominal variables is **Pearson's Chi-square** ($\chi 2$) statistic, which measures the statistical significance of the relationship between two variables. Acceptance of the null hypothesis means that there is no correlation between the studied variables.

The structure of the questionnaire The questions set up cannot be found in a previously validated questionnaire, so I considered it important to validate the entire questionnaire, for which I used **factor analysis**. Using factor analysis, I created a smaller number of new variables from several variables. Conditions for the feasibility of factor analysis:

- **Correlation matrix:** shows the correlations between the variables in the sample, the existence of which is an essential condition for factor analysis.
- **Anti-image matrix:** this allows the variables in the sample to be broken down into their explained standard deviation (image) and unexplained standard deviation (anti-image) based on their standard deviation. In factor analysis, this resolution is shown by the anti-image covariance / correlation matrices.
- **Bartlett test:** examines whether the variables in the population are uncorrelated, that is, whether the elements of the correlation matrix outside the main diagonal only

randomly deviate from zero. The condition of factor analysis is that the variables correlate with each other, preferably as strongly as possible.

- **Kaiser-Meyer-Olkin (KMO) criterion:** this criterion was used to examine the suitability of the variables for factor analysis. The higher the KMO test result, the better the factor analysis. A value below 0.5 should be considered unacceptable.

Cluster analysis tries to divide the sample through the dependent variables so that they form a common, homogeneous group based on certain properties. In the **K-mean procedure**, the cluster centers are determined as a function of the cluster number. The procedure is based on the calculation of the square root of the difference between the squares of the variables, ie the Euclidean distance (TAKÁCS ET AL., 2015).

I use **one-way analysis of variance** to explore the difference between each aspect. An analysis of variance (ANOVA) is an explanatory model and method that examines the effect of one or more independent variables on one or more dependent variables (SAJTOS - MITEV, 2007).

I used the method of PLS path analysis to set up the path model between the developed factors. A method that has been accepted and applied among many researchers and experts for decades, focusing on the study of the relationship between latent variables (KAZÁR, 2014; NAGY, 2018; ARANYOSSY - KULCSÁR, 2020). In the case of **PLS-SEM path analysis**, the interpretation of the reflective external model can be done using different criteria related to the reliability and validity of the measurement (*Table 2*).

Table 2: Criteria for reflective external model fit

Subject of investigation	Indicator	Calculation	Criterion	Source
Indicator reliability	Cronbach's alpha		Alpha > 0,7	CRONBACH (1951)
Structural reliability	Composition reliability indicator (CR)	$\frac{(\sum_i \lambda_i)^2}{(\sum_i \lambda_i)^2 + \sum_i \mathrm{Var}(\varepsilon_i)}$	CR > 0,7	WERTS-LINN-JÖRESKOG (1974)
Convergence validity	Average variance extracted(AVE)	$\frac{\sum_i \lambda_i^2}{\sum_i \lambda_i^2 + \sum_i \mathrm{Var}(\varepsilon_i)}$	AVE > 0,5	FORNELL - LARCKER (1981)

Discrimination validity	Fornell-Larcker-criterion	The square root of AVE values for each latent variable should be greater than the correlation coefficient between that latent variable and all other latent variables.	FORNELL - LARCKER (1981)
	Heterotrait-monotrait ratio (HTMT)	$\frac{\mathit{Average\ of\ pairwise\ correlation\ coefficients\ between\ manifest\ variables\ related\ to\ two\ latent\ variables}}{\mathit{Average\ of\ pairwise\ correlation\ coefficients\ beetween\ manifest\ variables\ related\ to\ the\ same\ latent\ variable}} \rightarrow \mathrm{HTMT}<0{,}9$	HENSELER-RINGLE-SARSTEDT (2015)

Source: Own editing, 2021.

HAIR ET AL. (2016), I used the Cronbach's alpha index to measure the reliability of latent variables, which should exceed 0.7. To check the convergence validity, the standardized factor weights (> 0.5) and the **compositional reliability index of the model** (Composit Reliability - CR> 0.7) must also be examined. In addition, the **mean explained variance** (Average Variance Exctracted - AVE> 0.5) was used in the dissertation.

Based on the FORNELL - LARCKER (1981) test, which is the **Fornell-Larcker criterion**, I performed the discriminant analysis, according to which the AVE value of a given latent variable should be higher than the square of the correlation between the other latent variables. The **HTMT correlation ratio** (heterotrait-monotrait) shows the quotient of the average of the pairwise correlation coefficients between manifest variables associated with two latent variables and the average of the pairwise correlation coefficients between manifest variables associated with the same latent variable. HENSELER ET AL. (2015), it is sufficient to assume discriminant validity if the values of the HTMT indices are below 0.9. I also tested the analysis of multicollinearity using the VIF (Variance Inflation Factor) index, in which case the goal was to keep the VIF value below 5 in all cases.

After analyzing the external model, the question arises as to whether the direct relationships found in the model are significant. The evaluation of the structural model was analyzed using a five-step procedure, which includes: evaluation of effect magnitude (f^2)), goodness of fit, determination of predictive relevance (Q^2), and analysis of path model coefficients (*Table 3*).

Table 3: Criteria for the fit of the internal, structural model

Subject of investigation	Indicator	Criterion	Source
Evaluation of effect magnitude	f^2	Kicsi: $0{,}02 < f^2 < 0{,}15$ Közepes: $0{,}15 < f^2 < 0{,}35$ Nagy: $0{,}35 < f^2$	HENSELER ET AL. (2009)
Goodness of fit	$GoF = \frac{AVE}{R^2}$	Kis minta: 0,10 Közepes minta: 0,25 Nagy minta: 0,36	FORNELL - LACKER (1981)
Predictive relevance	Q^2	$Q^2 > 0$	CHIN (1988)
Path model coefficients	β	p érték < 0,05	HAIR ET AL. (2011)

Source: Own editing, 2021.

I was able to write the **regression equations** using the path model coefficients, since the path model is a series of essentially overlapping regression models, where we break down the zero-order linear correlation between the independent and the dependent variable into two parts: the direct effect of the independent variable on the outcome variable; the effect of the independent variable on the dependent variable through intermediate variables (LAMPERTNÉ AKÓCSI, 2013).

The **Importance Performance Matrix Analysis** (IPMA) aims to identify historical variables that are relatively important for target constructs (i.e., those that have a strong overall effect) but also relatively low-performing (i.e., have low average factor values). . The aspects underlying these constructions represent potential areas for development that can be given a lot of attention. IPMA compares the total effect of each variable in the model with the factor values associated with the latent variable for a given construct (HAIR ET AL., 2016).

4. MAIN FINDINGS OF THE DISSERTATION

4.1. Analysis of factors of food production companies, results

In examining the use of Industry 4.0 technologies, I collected data from the questionnaire survey on the strategic goals of food companies, factors hindering and supporting development, industry 4.0 risks, sustainable economic, social and ecological factors, and changes in business performance.

As a first step, I identified the developments, Industry 4.0 tools, and factors influencing business performance and their indicators, which I was helped to gather by literature sources and consultations with company executives. The factors in the structural model are:

Factor 1: Strategic Objectives (SC)

Factor 2: Obstacles (AT)

Factor 3: Supporting factors (TT)

Factor 4: Industry 4.0 Risk Factors (IK)

Factor 5: Sustainable Industry 4.0 (FI)

a. Economic factors (FIG)

b. Social factors (FIT)

c. Ecological factors (FIO)

The dependent latent variables are:

Factor 6: Development / Investment Development (FB)

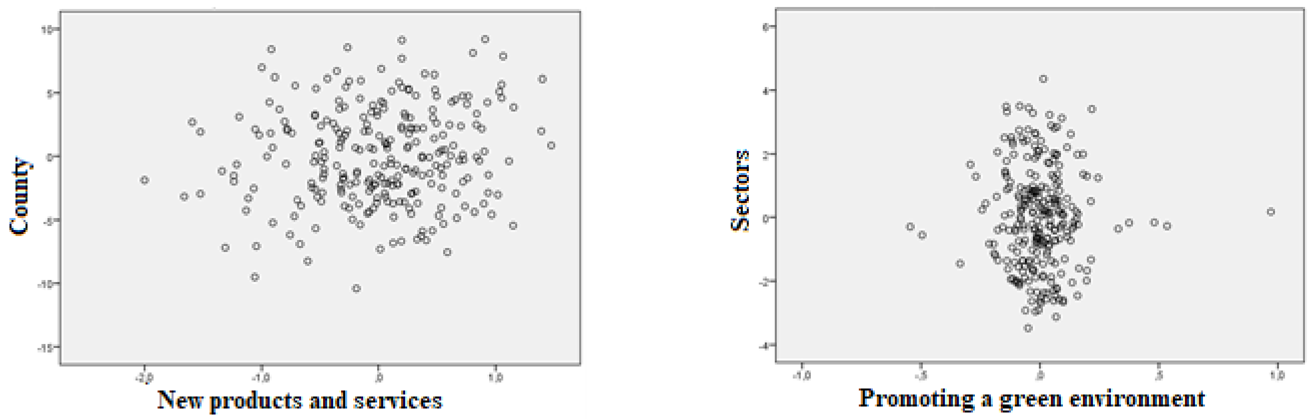
Factor 7: Using Industry 4.0 Tools (IE)

Factor 8: Business Performance (UT)

In order to validate the indicators in the questionnaire, I performed a factor analysis on the data. The validity of the principal components was analyzed with the latest available version of IBM SPSS Statistics 23. The indicators in the questions, which had a low value in the model, were removed after performing the factor analysis.

For the factor analysis, I used the a priori criterion, the essence of which is that I can decide on the number of factors before starting the factor analysis, and there can be a maximum of as many factors as there were initial variables. In my research, I had more than 119 variables, and during the development of the factors and removing outliers, a total of 112 variables remained from the sample, which I classified into 19 factors. The number of factors was determined by me, which was based on the literature research and the development of each topic.

It is important for the study to know what distribution the variables follow. For each variable, I thought I would discover a normal distribution, the graphical representation of which is shown in *Figures 3*.



a) New products, services and the relationship between counties **b) Promoting a green environment and the relationship between sectors**

Figure 3: Relationships and distributions variables

Source: Own editing, 2021.

A *3.a. Figure* 1 shows the classification by county and the relationship between the variable new products and services. Based on this, it can be said that the majority of the respondents marked above-average values per county, ie they want to develop a product and service and create a new one. A *3.b. Figure* 5 shows that the sectors unanimously responded that Industry 4.0 technologies are designed to support the green environment.

One of the most important metrics for judging whether variables are suitable for factor analysis is the KMO criterion. The KMO test shows the level at which the variables individually show partial correlation. The value ranges from 0 to 1, the larger, the more suitable the sample for factor analysis. Looking at the whole sample, the KMO test showed a value of 0.838, which confirmed that the sample was suitable for factor analysis, and even a value above 0.8 was considered very good (*Table 4*).

Table 4: KMO and Bartlett test results

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**,838**
Bartlett's Test of Sphericity	Approx. Chi-Square	21921,563
	df	7021
	Sig.	,000

Source: Own editing, 2021.

The Anti-image covariance and correlations matrix indicates the reliability of the sampling required for factor analysis. It can be used to separate the standard deviation of variables into explained and unexplained standard deviations. The values in the diagonal of the factor related to the use of Industry 4.0 tools are close to 1 in my model, which means that the variables are estimated by the other variables without error.

During the factor analysis, I determined the weights assigned to each indicator. Subsequently, values close to and below 0.4 were removed from the model, which were SC4, SC5, SC10, TT2, FIG1, FIT5, FIT7. After removing the low values, I ran the factor analysis again for each factor.

After the validation of the factors and indicators, I performed a cluster analysis and then a PLS-SEM path analysis with the generated factors.

4.2. Clustering of food companies

Based on my research, it can be said that food companies can be classified into clusters based on 3 main criteria: innovation, sustainability, risk factors. Based on each aspect, I have created 3-3 clusters, thanks to which it either supports or is neutral towards the given aspect or completely withdraws from it.

4.2.1. Clustering of food companies based on their innovation investment

Clustering was performed using the non-hierarchical grouping method, the K-means method. After testing the 2, 4 and 5 cluster solutions, I decided on the 3 cluster solution because for these clusters, the F test did not lead to an acceptable result.

The results of the analysis show that for food companies, 3 groups can be distinguished, taking into account business performance, the use of Industry 4.0 tools, supportive factors, and barriers (*Table 5*).

The first “innovative” cluster includes conscious food companies that pay attention to business and the use of Industry 4.0 tools, accounting for 43% of the sample. For these companies, high business performance is the goal, they make significant use of Industry 4.0 tools, take advantage of factors that support development, and consider barriers to a significant extent (.343).

The algorithm classified 54% of the sample in the second large group (“retainers”). Food companies in this group strive to maintain the current situation, ie their goal is to adapt to market needs, but do not plan large-scale investment.

The third cluster (“retreats”) included companies that pay below-average attention to supporting factors, have the least focus on increasing their business performance, and use Industry 4.0 tools, but not to the extent that they should.

Table 5: Development of innovation clusters of food companies

	Clusters		
	Innovative	**Retainers**	**Retreats**
UT_FACT	,343	-,202	-1,769
IE_FACT	,614	-,423	-1,703
TT_FACT	,454	-,219	-3,448
AT_FACT	,588	-,396	-1,842
Összesen	**113**	**140**	**6**

Source: Own editing, 2021.

The ANOVA table can be used to determine which variable best differentiates between clusters (*Table 6*). Based on the F value, it can be said that the factors supporting the investments have the highest F value, 119,565, which means that this variable had the greatest influence on the formation of the clusters. The F value of the business performance factor is 46,767, which shows that the factor has the least effect on the formation of clusters.

Table 6: Examination of differentiation between innovation clusters

ANOVA						
	Cluster		**Error**			
	Sum of squares	**df**	**Sum of squares**	**df**	**F**	**Sig.**
UT_FACT	18,886	2	,404	256	46,767	,001
IE_FACT	42,551	2	,527	256	80,806	,001

TT_FACT	50,674	2	,424	256	119,565	,001
AT_FACT	40,655	2	,573	256	70,939	,001

Source: Own editing, 2021.

Based on Pearson's Chi-square value of 10,595 and a significance greater than 0.05, it can be stated that the clustering of sectors cannot be clearly established. Similarly, there is no significant relationship between the company's ownership structure (p = 0.438), legal form (p = 0.103), number of employees (p = 0.154), net sales (p = 0.720) and the three clusters formed.

I examined whether there is a link between the clusters formed and how long the company has been in business. Based on the results of the study, the null hypothesis that there is no relationship between the variables can be rejected, as the value of Pearson's Chi-square is 19,811 and its significance is 0.003. According to them, a significant correlation can be established between the duration of business activity and the clusters (*Table 7*).

Table 7: Relationship between food innovation clusters and duration of business activity

	Value	Degree	Asymptotic significance
Pearson's Chi-square	19,811	6	**0,003**
Probability ratio	15,852	6	0,015
Linear relationship indicator	5,957	1	0,015

Source: Own editing, 2021.

Thanks to the cross-tabulation analysis, the relationship between the duration of business activity and innovation clusters shows that 69% of innovators have a business activity over 5 years, which means that it is important for these companies to monitor continuous improvement and innovation. This finding is supported by my first hypothesis that the vast majority of companies in the innovative food production cluster have more than 5 years of business experience.

H1: The vast majority of companies in the innovative food production cluster have more than 5 years of business experience.

4.2.2. Clustering of food companies based on sustainability factors

In the case of clustering according to sustainable economic, social and ecological factors, I classified the companies into the following 3 categories. The first category is “sustainability-loving,” which accounts for 43% of the sample. These companies are also keen to invest in the use of biodegradable materials and the installation of solar panels to promote renewable energy, as well as the development of social factors, ie enabling their employees to acquire new types of skills. The results support that the companies that like sustainability are located in Budapest (26.5%) and Pest county (12.4%), as well as in Szabolcs-Szatmár-Bereg county (17.7%) and Heves county (13.3%). 53% of the sample belong to the sustainability neutral group, which seeks to maintain the status quo. These companies operate mostly in Budapest, Pest county and Heves county. The third group includes “sustainability avoiding” companies, which make up 4% of the sample. These companies come from different areas (Hajdú-Bihar county, Bács-Kiskun county, Budapest) and deal with different sectors (mill products, meat processing, preservation and production, fruit and vegetable processing). The research also analyzed the year of business activity of food manufacturing companies and the relationship between companies monitoring sustainability. Hypothesis H2 should be rejected, that the more time a food company has been in business, the more it pays attention to sustainability factors.

H2: The more time a food company has been in business, the more it pays attention to sustainability factors.

4.2.3. Clustering of food companies based on risk factors

Based on the grouping of risk factors (financial, technological, operational, economic, personnel, legal, environmental, market, business), I also classified the companies into three categories: risk takers, risk averse and risk neutral. The first group includes “risk takers” who make up 29% of the sample. These companies are least afraid of financial problems because their business performance is also well above average. The largest part of the sample (45%) can be classified into the risk-neutral group, whose goal is to keep the current situation taking into account the risk factors. The third cluster includes “risk-averse” companies, which are primarily afraid of political and legal decisions, as well as personal issues such as job transformation, labor shortages, and inadequate staff qualifications. The risk clusters can be said to have no relation to the general information about the company, ie location, industry, ownership structure, legal form, number of employees, annual net sales and duration of business.

4.3. PLS-SEM results and hypothesis testing

4.3.1. Evaluation of the external model

During the PLS algorithm, I examined the internal consistency of each factor with the Cronbach's alpha index, which underestimates the degree of internal consistency, as it assumes that all variables have the same factor weight. This problem is eliminated by the Composite Reliability Indicator (CR), which also takes into account the factor weight values assigned to the variables, so its value must already exceed 0.7. In the model, these expected values are met, and moreover, for all factors, the composite reliability index is higher than the Cronbach's alpha index (*Table 8*).

The AVE value should be above 0.5, the higher the more the latent variable retains the variance of the manifest variables. For business performance, a value above 0.6 is considered very high, which means that the input (manifest) variables (Industry 4.0 assets and Sustainable Industry 4.0) retain more than 60% of their variance in business performance.

Table 8: Results os Cronbach's alpha, CR and AVE indicators of factors using the SmartPLS software package

Factors	Cronbach's alpha	CR	AVE
Strategic goals	0.715	0.801	0.369
Obstacles	0.878	0.900	0.452
Supporting factors	0.785	0.849	0.487
Developments / investments	0.985	0.987	0.916
Sustainable Industry 4.0_Economic factors	0.788	0.846	0.440
Sustainable Industry 4.0_Social factors	0.813	0.867	0.528
Sustainable Industry 4.0_Ecological factors	0.930	0.944	0.682
Industry 4.0 tools	0.843	0.877	0.418
Industry 4.0 risk factors_Economic risk	0.764	0.850	0.586
Industry 4.0 risk factors_Legal risk	0.800	0.869	0.624
Industry 4.0 risk factors_Environmental risk	0.791	0.878	0.707

Industry 4.0 Risk Factors_Operational Risk	0.776	0.856	0.598
Industry 4.0 risk factors_Market risk	0.788	0.855	0.541
Industry 4.0 risk factors_Financial risk	0.841	0.884	0.560
Industry 4.0 Risk Factors_Personal Risk	0.833	0.876	0.503
Industry 4.0 risk factors_Technological risk	0.795	0.859	0.551
Industry 4.0 Risk Factors_Business Risk	0.796	0.867	0.621
Business performance_Profitability indicators	0.790	0.864	0.614
Business performance_Growth trend indicators	0.824	0.883	0.654

CR: Composite reliability, AVE: Average Variance Extracted.

Source: Own editing, 2021.

Based on the results of the Fornell-Larcker criterion, it can be said that in the case of the barrier factor, the highest value among the industry 4.0 risk factors was given to financial risk (0.672), which means that the barrier factor is most closely related to this factor. Furthermore, the results also show that the AVE square roots of the model are higher in all cases than the correlation of all reflective constructs, so the criterion of discriminant validity is met.

Using a heterotrait-monotrait ratio (HTMT), I examined the correlation measure for each pair of latent variables. The result shows that each HTMT index value is below 0.9, which means that the discriminant validity is met.

Multicollinearity analysis was tested using the VIF (Variance Inflation Factor) index. Based on the results, it can be said that the exogenous latent variables also meet the maximum threshold of 3.3 set by DIAMANTOPOLOS - SIGUAW (2006) if the use of biodegradable materials (packaging) (FIO4) does not meet the indicator value of 4.012. we take into account. The exogenous variables range from 1.163 to 2.792, with the exception of the FIO4 indicator, which means that there is no multicollinearity between the factors.

Based on the above analyzes, based on the Cronbach's alpha index, composite reliability index (CR), mean explained variance (AVE), heterotrait-monotrait ratio (HTMT) and multicollinearity (VIF), the external model is acceptable, thus, the data are suitable for the analysis of the structural model.

4.3.2. Evaluation of the internal model

The evaluation of the structural model was analyzed using a five-step procedure, which includes: evaluation of effect magnitude (f^2), goodness of fit, determination of predictive relevance (Q^2), and analysis of path model coefficients.

To evaluate the magnitude of the effect, I used the 5000 subsample bootstrap sampling, thanks to which I determined the small, medium, and large effects of the variables on the target variable. If it ranges from around 0.02 or below 0.15, it can be considered a small impact magnitude, which in the case of the model had two such effects: an impediment and between developments, investments, and between developments, investments, and Industry 4.0 devices. Values around or above 0.15 show a medium magnitude of impact, which was also characteristic of two relationships in my model: between strategic goals and development, investments, and between Industry 4.0 assets and business performance. Large effects are considered to be around 0.35 or higher. Based on this, it can be said that there is a large relationship between support factors and strategic goals, between sustainability and Industry 4.0 instruments, and between risk factors and barriers.

The Goodness of Fit (GoF) index can be calculated as the mean of the mean explained variance and the mean R^2. Model fit goodness index: 0.571 x 0.269 = 0.154. In the research, the criteria of good fit are met, as the value is above the minimum requirement for a small sample (0.10).

When testing predictive relevance (Q^2), my Q^2 value is greater than zero in all cases, so it can be said that the research model has predictive relevance. Predictive relevance in terms of barriers is 0.410, in terms of strategic goals 0.267, in Industry 4.0 assets 0.262, and in terms of business performance 0.178, which means that the model is acceptable.

4.3.3. Direct and indirect effects in the model

The results of the direct effect of bootstrapping are summarized in *Table 9*.

Table 9: Bootstrapping results of the internal model: direct effect

Path	Direct effect coefficient	Sample average	t statistic value	p-value
Obstacles → Developments / investments	-0.145	-0.144	2.009	0.045
Obstacles →Strategic goals	0.033	0.038	0.556	0.579
Developments / investments →Industry 4.0 assets	0.112	0.109	2.036	0.042
Sustainable Industry 4.0 →Industry 4.0 tools	0.433	0.436	6.981	0.000
Sustainable Industry 4.0 →Business Performance	0.340	0.343	3.657	0.000
Industry 4.0 Tools →Business Performance	0.187	0.190	2.054	0.040
Industry 4.0 Risk Factors →Industry 4.0 assets	0.184	0.185	2.960	0.003
Industry 4.0 Risk Factors →Obstacles	0.648	0.650	13.595	0.000
Strategic goals →Development / investment development	0.156	0.158	1.898	0.058
Supporting factors →Development / investment development	0.032	0.038	0.379	0.705
Supporting factors →Strategic goals	0.545	0.560	10.501	0.000

Source: Own editing, 2021.

Based on the analyzes, it can be written what and how it affects the Industry 4.0 devices in the model, as well as business performance:

Strategic goals = 0.545 x Supporting factors

Supporting factors have a direct, significant impact on strategic goals.

Development of developments = -0.145 x Obstacles + 0.156 x Strategic goals

The opposite sign of the impediments suggests that it has an effect on the development of developments and investments, but has a negative effect on them (-0.145). The more barriers there are, the less companies will invest in new technology tools. Obstacles directly affect developments, but do not affect the development of strategic goals (p = 0.579). Developments and investments are also influenced by the company's strategic goals.

Industry 4.0 assets = 0.112 x Developments + 0.433 x Sustainable factors + 0.184 x risk factors

As the direct impact coefficient is 0.112, it can be stated that developments and investments have a direct impact on the use of Industry 4.0 tools, which means that if a food company thinks about developing its individual areas, there is a significant chance that one of the Industry 4.0 tools (ek) will invest. The economic, social and ecological factors of Sustainable Industry 4.0 are indeed related to new technological tools and also have a direct impact on business performance.

Business Performance = 0.340 x Sustainable Factors + 0.187 x Industry 4.0 Assets

Industry 4.0 devices clearly state that they have a positive, direct impact on business performance. The more Industry 4.0 tools a company uses, the more its business performance will increase. Sustainability factors have a greater impact on business performance than Industry 4.0 devices.

Obstacles = 0.648 x Risk factors

Examining the 9 main risk factors, I came to the conclusion that these factors have the greatest impact (0.648) on the barriers, i.e., respondents consider the risk factors to be the barriers. Risk factors also directly affect the use of Industry 4.0 tools. Interestingly, risk factors only affect business performance through Industry 4.0 tools, not directly.

Table 10: Bootstrapping results of the internal model: indirect effect

Path	Indirect effect coefficient	Sample average	t statistic value	p-value
Supporting factors → Strategic goals → Development / investment development	0.094	0.097	2.486	0.013
Sustainable Industry 4.0 →Industry 4.0 Tools →Business Performance	0.081	0.082	2.143	0.033
Risk →Obstacles →Developments / investments	-0.089	-0.085	1.900	0.048
Risk →Industry 4.0 Tools →Business Performance	0.034	0.037	1.597	0.111

Source: Own editing, 2021.

The results of mediation analysis show that there is a significant, indirect relationship between the constructs examined. The supporting factors affect the strategic goals, and the strategic goals have a positive effect on the developments and investments. The supporting factors do not directly (p = 0.705), but only indirectly, through the strategic goals, on the developments (*Table 10*).

Supporting factors are indirectly related to the development of developments and investments (p = 0.13), and sustainability affects business performance not only directly but also indirectly through Industry 4.0 tools.

Industry 4.0 risk factors directly affect the use of Industry 4.0 tools, but they also indirectly affect them through barriers and developments / investments. This relationship is a negative sign relationship, as the more risk and disincentives, the less the company invests in Industry 4.0 assets.

4.3.4. Interpretation of model results

According to the bootstrapping result, based on the literature, there were only two roads from the road model I set up where there was no significant relationship, namely the effect of supporting factors on developments and investments, as the direct effect coefficient is 0.032 and the p-value is 0.705. the effect of impediments on strategic goals ($\beta = 0.033$, $p = 0.579$).

Eliminating the relationship between the barriers and the strategic goals, as well as the relationship between the supporting factors and the development of investments / investments, the factors included in the model and the direct and indirect effects between the factors are shown in *Figure 4*.

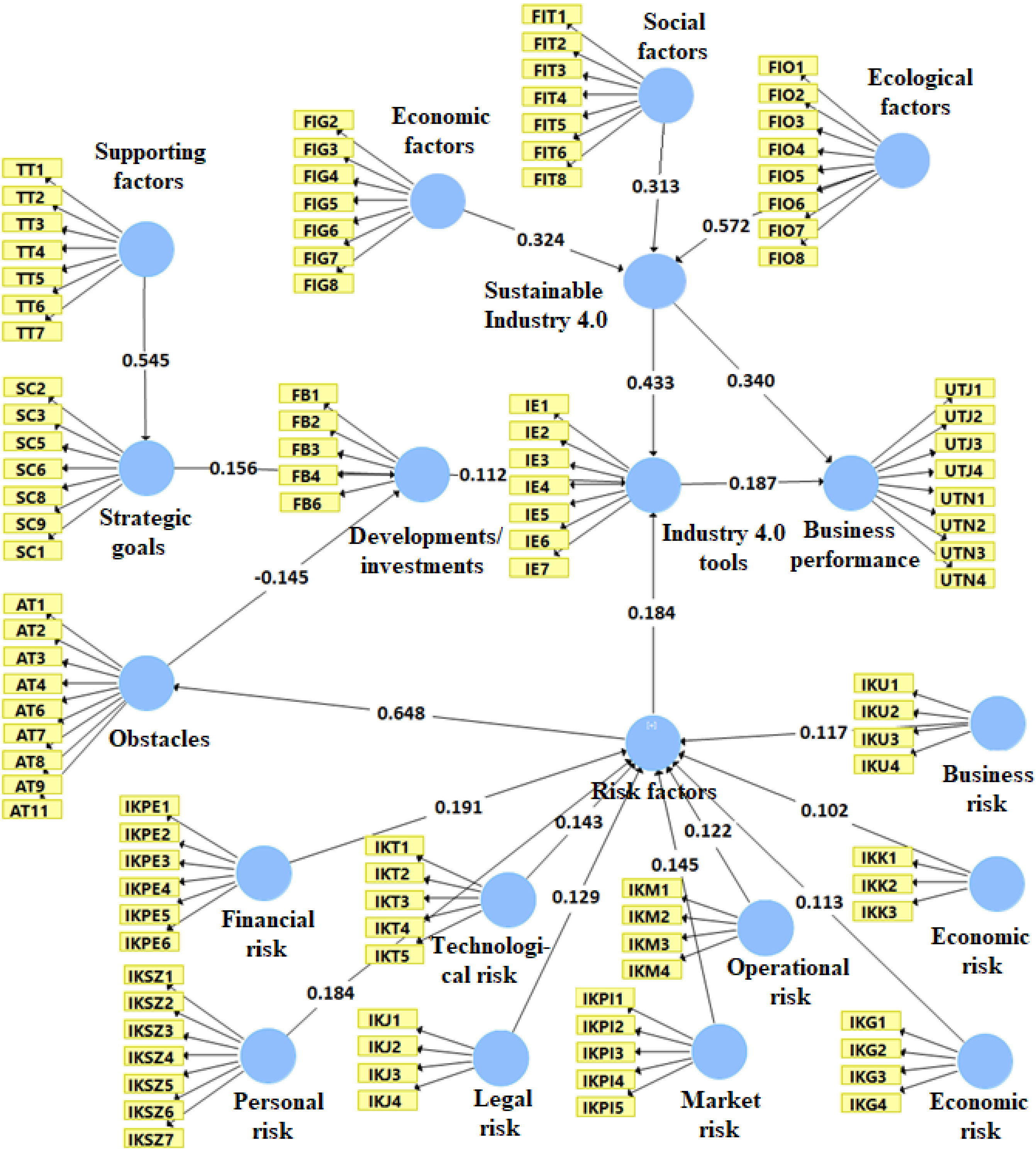


Figure 4: Direct and indirect effects in the model

Source: Own editing, 2021.

Based on this, it can be said that the supporting factors significantly influence the strategic goals and indirectly affect corporate development and investment. Obstacles have a negative effect on developments, meaning that the more obstacles a company has to face, the less it gets into developments. Among the obstacles, it should be emphasized that the biggest factor that prevents companies from investing in innovation tools is the high costs incurred and the lack of existing own resources. This may be related to each other, as if they had ample own resources for investment, they would perhaps be less bothered by the high costs incurred by food companies. Among other things, the lack of a skilled workforce should be mentioned as an obstacle, as this factor also has a significant impact on the development of investments.

H3: The extent of Industry 4.0 developments is negatively affected by high technology costs, lack of own resources and lack of skilled labor.

Other results of the analyzes include the finding that sustainability (economic, social, ecological factors) has a strong, significant impact on the increase of Industry 4.0 assets. If a food company wants to pay more attention to the ecological impact of the products it manufactures, it will introduce new technologies, thereby reducing the company's ecological footprint. Indeed, companies believe that new technologies reduce air pollution, use renewable energy, thereby reducing energy costs, use biodegradable packaging, increase product recycling, and Industry 4.0 devices are designed to support the green environment, as recycling reduces deforestation.

In the route model, Industry 4.0 technology tools have a particularly strong, positive, significant impact on business performance. The use of Industry 4.0 tools has a direct impact on business performance, meaning that the more a company uses new technology tools, the more it increases its business performance. These statements support the fourth hypothesis.

H4: The emergence of new tools and their use has a strong, positive, significant impact on the business performance of food companies.

When introducing Industry 4.0 tools, companies need to focus not only on sustainability factors but also on risk factors, as these factors can also significantly influence companies' strategic decisions and final investments.

4.3.4. Industry 4.0 tools and business performance importance performance matrix analysis (IPMA)

Further expanding the results of my dissertation, I performed an Importance Performance Matrix Analysis (IPMA) analysis to use Industry 4.0 tools and examine business performance. My goal with this was to identify historical variables that are of relatively high importance for the use of Industry 4.0 tools and business performance, i.e., they have a significant impact but have a relatively low factor value.

By standardizing the IPMA analysis for each indicator, it can be said that the sustainability factors for the use of Industry 4.0 devices have the greatest overall impact compared to the other constructs (*Figure 5*).

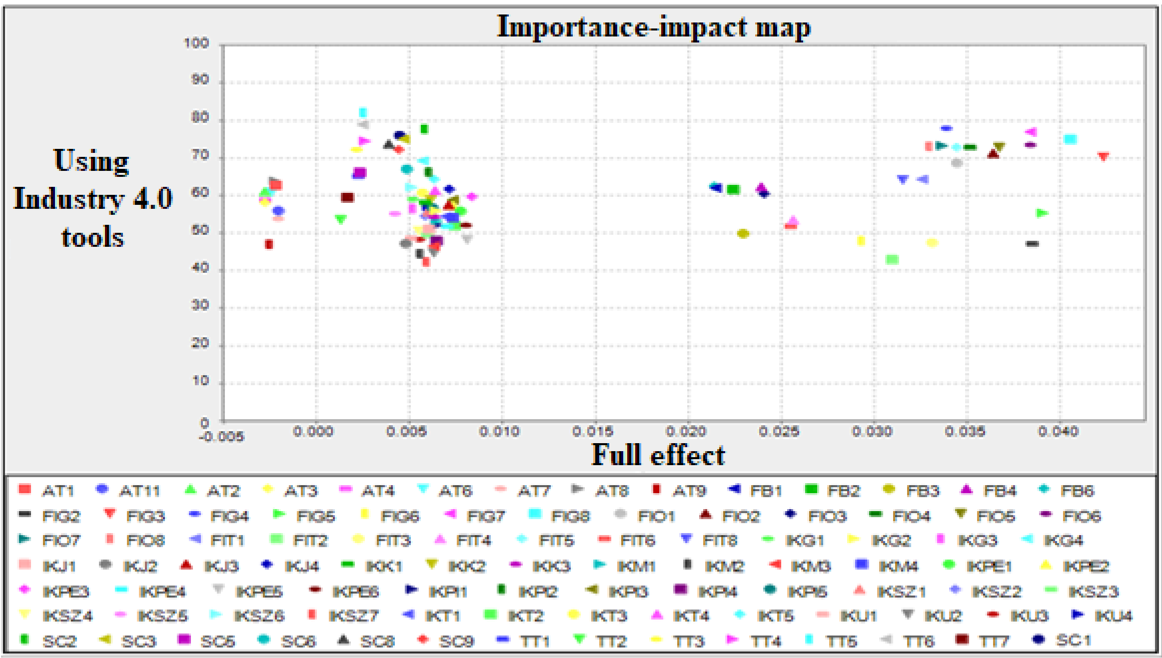


Figure 5: Importance-impact map: Using Industry 4.0 tools

Source: Own editing, 2021.

Among the sustainability factors, social factors have a significant influence, with emphasis on supporting new types of skills and qualifications (FIT5) and strengthening the idea that robots are designed to support workers (FIT3).

In addition to sustainability factors, risk plays the biggest role in purchasing an Industry 4.0 asset. Among the risk factors, the risk of technology failure (ICT4) primarily deters food companies from Industry 4.0 assets, and the hidden costs incurred (IKPE2) also have a significant impact on investment in innovative assets. According to them, Hypothesis 5 is acceptable, as it is indeed true that, among the risk factors, it is primarily the hidden costs and the risk of technological failures that deter food companies from new technological innovations.

H5: Among the risk factors, it is primarily the hidden costs and the risk of technological failures that deter food companies from new technological innovations.

Among the political and legal risk factors, the indicator of stricter tax and customs regulations (IKJ2) is the deterrent factor. When investing in Industry 4.0 assets, companies are less afraid that hidden costs will be high (IKPE2) or they will lose customers with new technology tools (IKPI1). They are also less afraid of environmental risk factors, such as difficulties arising from environmental regulations (IKK1), the costs of increased regulation of energy use (IKK2), or the adverse side effects of new technologies (IKK3).

When looking at business performance, sustainability factors also have the greatest impact on it (*Figure 6*). Among the sustainability factors, the recycling of the product (FIO5) and the "use of renewable energy (solar cells)" (FIO2) indicators are also of outstanding importance within the ecological factor.

H6: Of the sustainability factors, ecological factors have the most significant impact on business performance.

Among the Industry 4.0 factors, the biggest impact is between machine-to-machine communication (IE4), big data real-time data evaluation (IE3), robotics (IE1), and sensor technology (IE6).

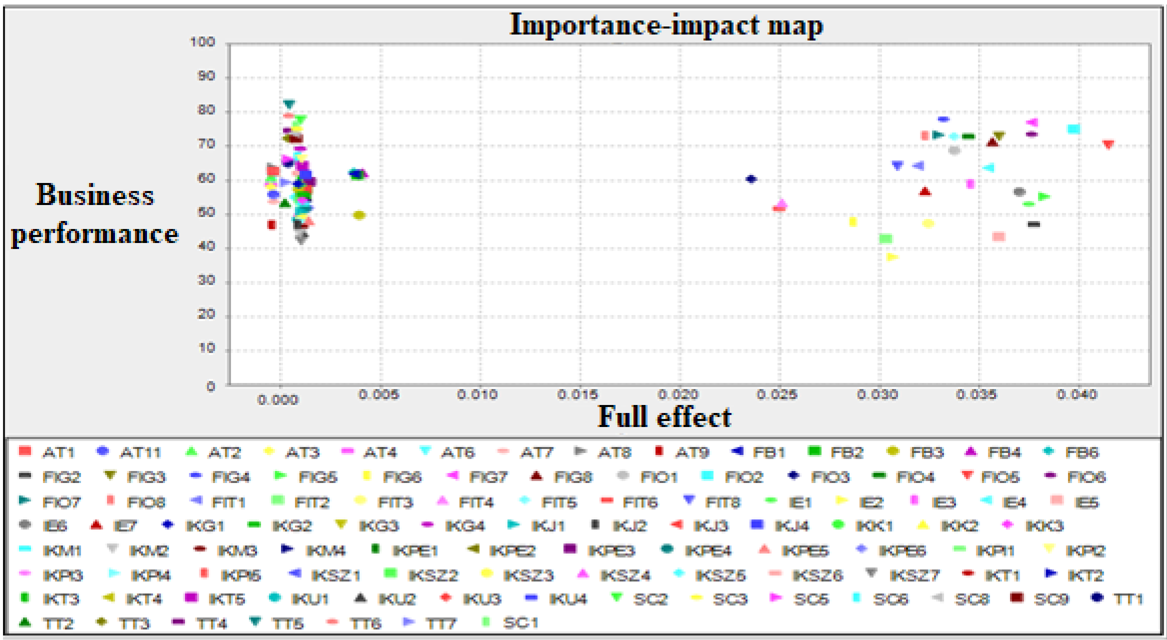


Figure 6: Importance-impact map: business performance

Source: Own editing, 2021.

Overall, the use of Industry 4.0 tools is significantly influenced by sustainability factors, so companies need to review and develop that area first. They need to pay attention to new types of skills and competencies and reinforce the idea that machines are designed to support workers. After that, it is worthwhile to deal with the use of air pollution reduction equipment, biodegradable packaging materials and the purchase of the necessary machines and equipment. In addition to sustainability factors, a number of risk factors also significantly affect the use of Industry 4.0 tools: the risk of technological failure, fear of hidden costs, regulatory costs.

In terms of business performance, companies should pay the most attention to reducing errors and increasing profitability within sustainability factors. The use of Industry 4.0 tools also has a significant impact on business performance, including machine-to-machine communication and data evaluation areas.

5. NEW AND RECENT FINDINGS OF THE THESIS

The overall objective of the dissertation is to assess the strategies and developments of Hungarian food production companies, to examine the factors hindering and supporting the developments, and to explore the uses of Industry 4.0 technologies. In my dissertation I pay attention to the analysis of external and internal risks, I examined the risk factors characteristic of food production companies, and how they affect the purchase and introduction of new tools directly or indirectly. Next, I analyzed the literature on sustainability factors (economic, social, ecological) and then the data collected, which may not only affect the use of Industry 4.0 technologies, but also result in improved business performance. The main goal of my research was how the following indicators directly and indirectly affect business performance: supporting factors, obstacles, strategic goals, implementation of developments, use of Industry 4.0 tools, sustainability factors and risk factors.

With the realization of the main and sub-objectives, I formulated the following new and novel results:

1. It can be said that food companies consider several Industry 4.0 devices to be important, of which the use of mobile-based devices and real-time data evaluation of Big Data are outstanding. Robotization, automated warehousing, and communication between machines are considered significant, as the development of these technological tools contributes significantly to a company’s competitiveness.
2. Industry 4.0 devices have significant advantages for the company: technological standards increase significantly, productivity, product range, product quality also start to increase. An exception to the growth is the issue of headcount and flexibility, as most respondents believe that headcount will not change and flexibility will not be better if the company invests in new assets.
3. Based on my research, it can be said that food companies can be classified into clusters based on 3 main criteria: innovation, sustainability, risk factors. The vast majority of innovative companies have more than 5 years of business experience. And companies with less than 3 years of business performance are reluctant, as they do not yet have enough capital to develop their business at the right pace.

4. Based on the relationship between the year of business of food production companies and the companies that monitor sustainability, the more time a food company has been in business for it, the more it pays attention to sustainability factors.
5. The risk clusters can be stated to have no relation to the general information about the company, ie location, industry, ownership structure, legal form, number of employees, annual net turnover and duration of business.
6. Obstacles have a direct impact on developments and investments, but have a negative effect on them (-0.145). The more barriers there are, the less companies will invest in new technology tools. Among the obstacles, it should be emphasized that the biggest factor that prevents companies from investing in innovation tools is the high costs incurred and the lack of existing own resources. Among other things, I must mention the lack of a skilled workforce as an obstacle, as this factor also has a significant influence on the development of investments.
7. Industry 4.0 tools have a direct, strong, significant impact on business performance, meaning that the more a company uses new technology tools, the more it increases its business performance.
8. New technologies also carry risk factors that influence the decisions of business leaders, and thus business performance. The results suggest that Industry 4.0 risk factors have a direct impact on the use of Industry 4.0 tools, but also indirectly affect them through barriers and developments / investments. This relationship is a negative sign relationship, as the more risk and disincentives, the less the company invests in Industry 4.0 assets.
9. Sustainability increases operational performance, efficiency and effectiveness, minimizes resource use and costs, and benefits society by offering less harmful products and services in the least possible form. Effectiveness includes the ability to sense and respond quickly to changes within the company and the environment. Sustainability factors have a positive, direct impact on business performance.
10. By standardizing the IPMA analysis for each indicator, it can be said that one of the biggest overall effects of the use of Industry 4.0 tools is the risk factors. Among the risk factors, it is primarily the hidden costs incurred and the risk of technology failure that deter food companies from Industry 4.0 devices.

11. In preparing the IPMA analysis of business performance and individual indicators, it can be said that one of the biggest influences on the growth of business performance is the sustainability factors, including ecological factors, of which product recycling and “renewable energy” are of paramount importance. energy use (solar panels) ”indicators.

6. PRACTICAL APPLICABILITY OF THE RESULTS

In my dissertation, I examined the possibilities of increasing the business performance of food companies in the light of digitalization and sustainability factors. Based on my results, the following practical suggestions have been formulated to improve the business performance of food companies:

1. In order for companies to develop a production schedule and an optimized process that has a significant positive impact on their business, it is essential to develop a long-term strategic goal in which significant development of technological tools is also of paramount importance.
2. When IT investments are used, production increases, and thus revenue and profits, as well as higher quality and performance, can be achieved with the introduction of new tools. The reliability and transparency of production processes and the quality of products increase. Thanks to the decision support systems, the awareness of the management increases, and the individual strategic decisions become more well-founded.
3. The use of Industry 4.0 tools also has a significant impact on business performance, including machine-to-machine communication and data evaluation. The use of big data helps managers to study internal and external factors and errors, so they can significantly affect productivity, efficiency and competitiveness by reducing negative effects and increasing positive ones.
4. Company managers and decision-makers must pay attention to sustainability factors, including ecological factors, which have a significant impact on business performance. These indicators include the use of biodegradable materials (packaging), the installation of solar panels to promote renewable energy, and the promotion of a green environment. If a company wants to stay competitive, it needs to pay close attention to both sustainability factors and Industry 4.0 assets.
5. I propose the development of a strategic plan aimed at promoting the optimal and sustainable use of natural resources, the importance of the principles of the circular economy, which has a positive significance for the environment.

6. I also consider the development of social factors to be important, ie to enable employees to acquire new types of skills and to accept the notion that robots and machines do not displace but support the monotonous work of employees.
7. Effectiveness includes the ability to perceive and respond quickly to changes in the company and the environment, risks. Companies face the following risk factors: high hidden costs, increasing technological risks, the importance of data security, rising raw material and energy prices, job transformation, and so on. If they are able to prepare for internal and external risk factors and then consider the potential growth and risk involved, feel free to embark on developments, as they can gain a significant competitive advantage if they have the right expertise and technological tools.
8. I also recommend that investment and labor subsidies be used as efficiently as possible.

I summarized the proposals at the government level in the following points:

1. Governments should enact policy support instruments that ensure greater development of industries, businesses, economies, encourage investment in Industry 4.0 technology tools, thereby reducing the gap between developed and developing countries.
2. Different legal regulations greatly influence the investment opportunities of companies, tax incentives further contribute to the incentives of companies wishing to develop.
3. Launch education and training programs for the food companies involved.
4. Providing support to experienced, successful businesses for international expansion.

The activity of publications in recent years shows that innovation and efficiency will continue to be a central issue in the production of companies, and various publications and debates will contribute to the further theoretical and practical development of these areas.

7. LIST OF PUBLICATIONS RELATED TO THE DISSERTATION

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Subject: PhD Publication List

Candidate: Edina Erdei
Doctoral School: Károly Ihrig Doctoral School of Management and Business
MTMT ID: 10063904

List of publications related to the dissertation

Articles, studies (20)

1. Oláh, J., Popp, J., **Erdei, E.**, Kovács, S.: A gazdasági és pénzügyi kockázatok értékelése a visegrádi együttműködés országainak és Szerbia kis- és középvállalatainál.
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Total IF of journals (all publications): 2,592
Total IF of journals (publications related to the dissertation): 2,592

The Candidate's publication data submitted to the iDEa Tudóstér have been validated by DEENK on the basis of the Journal Citation Report (Impact Factor) database.

10 May, 2021

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