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EXPLORING DIGITAL MATURITY PERCEPTION VS. REALITY IN HUNGARIAN SMES

Adam Péntek [1], Sándor Kovács [2], András Helmeczi[3] Tamás Kovács[1]

[1] University of Debrecen, Faculty of Economics and Business Administration, Institute of Methodology and Business Digitalisation, Hungary

[2] University of Debrecen, Faculty of Economics and Business Administration, Centre for Social Sciences Coordination and Research, Debrecen, Hungary

[3]University of Debrecen, Faculty of Economics and Business Administration, Institute of World Economics and International Relations, Hungary

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Abstract

The research aimed to explore how the digitalisation development of micro, small, and medium-sized enterprises (SMEs) in Hungary relates to their perceived digital readiness, and what role the size of the enterprise plays in this relationship. During the data collection, structured questionnaire data were collected from 207 enterprises, which were analysed using the Partial Least Squares Structural Equation Modelling (PLS-SEM) method. The reliability of the measurement model was adequate (Cronbach alpha: 0.728–0.915; AVE: 0.579–0.792), and the discriminatory validity was verified by several procedures (e.g., HTMT values: 0.425–0.641). According to the results of the structural model, actual digitalisation had a negative, significant relationship with perceived digital readiness (β = -0.444; $p < 0.001$) and perceived adaptability (β = -0.501; $p < 0.001$). The size of the enterprise also had a significant impact on the perception of adaptability (β = 0.363; $p < 0.001$) and also played an intermediary role in the model. The results suggest that more advanced businesses are more critical of their situation, while smaller companies tend to overestimate their digital capabilities. The research contributes to a deeper understanding of the distortions of digitalisation self-assessment and the foundation of targeted development interventions.

1. Introduction

According to the data of the Central Statistical Office, micro, small, and medium-sized enterprises (MSMEs) are the most essential players in Hungary in terms of the number of operating enterprises and the proportion of employees. However, the penetration of digital technologies varies significantly by company size: while large companies and multinationals tend to adapt quickly to new information and communication technologies (ICTs), smaller companies often lag in their adoption. These differences are driven by factors such as scarce financial resources, lack of IT expertise, constraints in the company culture, or an inadequate support environment (KSH, 2023; Sándor & Gubán, 2021; Chinedu Eze et al., 2021).
The dynamic development of digitalisation requires us to regularly review businesses from the point of view of infrastructure, human readiness, and IT, and to examine the differences between real and perceived digital readiness. The discrepancy between real and perceived digital maturity can highlight points that may hinder the effective integration of ICT tools into business processes. Some businesses may overestimate their digital capabilities, while others may underestimate their digital capabilities, leading to incorrect strategic decisions, resource

1 Contact Author. Tel.: +36 20 423 5361
Email address: kovacs.sandor@econ.unideb.hu

allocation errors, and competitive disadvantage. In the rapidly changing digital environment, such studies must be carried out using objective, structured, and empirical methods, so that the real situation and development opportunities of businesses can be accurately mapped (Csordas & Fuzesi, 2019; Fan & Ouppara, 2022).

This study aims to examine the digital readiness of micro and small enterprises in Hungary, with special regard to the differences between the perceived and actual levels of digitalisation. In the course of the research, primary data collection was carried out based on a questionnaire survey, during which the respondents evaluated the IT equipment use and digital strategy of their own company, as well as the related organizational competencies. To analyse the collected data, we used the PLS-SEM (Partial Least Squares Structural Equation Modelling) method, which is part of structural equation modelling, which allows the exploration of complex relationships, latent variables, and causal relationships on non-normal distribution and smaller sample sets. This methodological approach is particularly suitable for providing a nuanced picture of the factors influencing digital maturity and the differences between the subjective and objective states of enterprises.

2. Literature review and hypotheses

The spread of digital technologies has fundamentally transformed the functioning of the economy in the past decade. ICT tools and digital solutions are no longer just complementary tools, but have become essential for business operations (Wong & Kee, 2022). Digital technology also enables faster decision-making, more efficient resource management, and more flexible customer relationship management. This is particularly important for micro and small enterprises (MSMEs), which often operate with scarce resources, limited market knowledge, and low organizational capacity.

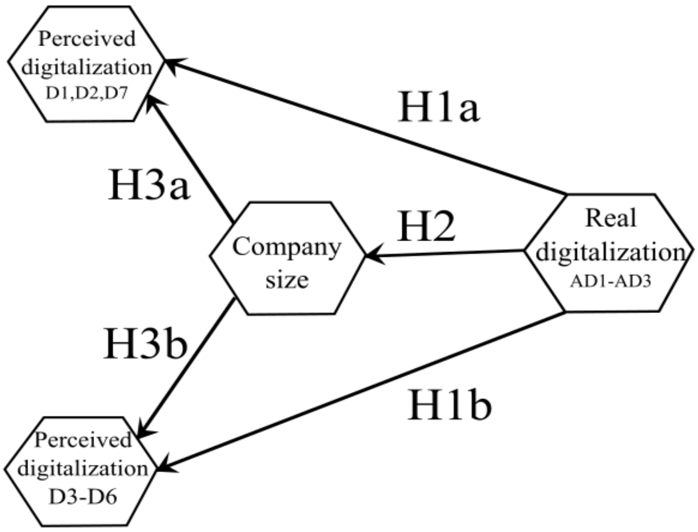
The concept of digital maturity is a complex indicator that encompasses access to ICT tools, their actual use, the existence of digital competences, and the attitude of company management towards digitalisation (Csordás & Füzesi, 2019; Gurría, 2019; Kő et al., 2023). In the international literature, several models have appeared to measure digital maturity, which usually take into account structural and cultural components as well. Therefore, when interpreting digital maturity, it is not enough to examine only the existence of devices or the level of development of the IT infrastructure. Adaptation at the organizational level, embedding in the strategy, and the managerial approach are at least as decisive factors.

However, in the context of digital maturity, it is important to distinguish between the actual and perceived digital state. A growing body of research shows that CEOs and employees often do not have an accurate sense of their organization's digital maturity. Management may overestimate the results achieved, as having a website or social media presence already represents a significant improvement for the company. However, in reality, these tools may not be connected to other key business processes, such as customer relationship management (CRM), enterprise resource planning (ERP), or online sales. Digitization is thus often present in a fragmented way (Valaskova et al., 2025). It is implemented in some areas, while it is completely absent in other functions. This results in a gap between the perceived and actual maturity levels (Fernández-Portillo et al., 2020; C. Zhang et al., 2022).

The deviation is not only a theoretical curiosity, but also has practical consequences. If an organization overestimates its digital maturity, it may not pay enough attention to further developments, lack innovation, or fail to detect market challenges in time. On the other hand, undervaluation can lead to a defensive strategy and excessive risk aversion, which also hinders development. Digital self-esteem is therefore not just a psychological or attitudinal issue, but can have a direct impact on the competitiveness, adaptability, and market presence of a company (Ortiz de Guinea & Raymond, 2020; Park & Hong, 2016).

Based on domestic and EU statistics, the lag of Hungarian MSMEs in the field of digital transformation has been mapped. According to the DESI index, Hungary ranked 26th out of 28 EU member states in 2020 in terms of business digitization and e-commerce. Progress is challenging (European Commission, 2022). It can be observed that while the technological infrastructure is gradually evolving, the deeper components of digital maturity, such as the internal company culture or the integration of digital strategies, are much more difficult.

Another aggravating factor may be that businesses are often unaware of the opportunities that modern digital solutions would open up for them. Limited human resources, a lack of management digitalisation skills, and a fear of innovation all contribute to slow adaptation (Lassnig et al., 2018; Švarc et al., 2020).
Several researchers emphasize that increasing digital readiness is not only a technological issue, but a complex organizational and strategic task that affects the entire operation of the company (Csedő et al., 2019; Irimiás & Mitev, 2020; Sommer, 2015). In order for the digital transition to be successful, technological investments must also go hand in hand with awareness-raising, training, and the encouragement of organizational learning. Businesses should interpret digitalisation not as a one-off IT project, but as a continuous, organization-level change.
Along with these theoretical considerations, the present research aims to explore the extent to which the digital maturity perceived by managers differs from the actual, objectively assessed digital level in the case of micro and small enterprises in Hungary. The accuracy of corporate self-assessment can fundamentally influence the effectiveness of digital developments, so we formulate the following hypotheses(Figure 1) :
H1: The actual level of digitalisation has a significant relationship with the digital readiness perceived by enterprises.
H2: The perception of digital readiness among larger (small or medium) enterprises differs significantly from that of micro-enterprises.
H3: The size of the enterprise acts as an intermediary between the actual level of digitalisation and self-assessed adaptability
The examination of these hypotheses will be carried out in the framework of the empirical research presented in the next chapter.



1. Figure Hypotheses and theoretical model of the research
Source: My edit

3. Aim, methodology, and data of the research

The research aimed to examine the digital readiness of micro and small enterprises in Hungary, with special regard to the differences between the perceived and actual levels of digitalisation. The study used structured quantitative methods, including Partial Least Squares Structural Equation Modelling (PLS-SEM), to find out how companies' self-esteem and real digital state relate to each other, and to what extent company size mediates the relationship between them. The questionnaire used for the surveys was developed based on semi-structured interviews with three companies in Hajdú-Bihar county that are experienced in digital technologies. The questionnaire compiled based on the interviews measured the perceived digitalisation, the actual technological and human capacities, and the infrastructural conditions in a structured form. The questionnaire was collected in the autumn of 2021 and the beginning of 2022; Out of the 300 questionnaires distributed, we received 180 evaluable answers. Data collection was carried out on paper through a personal visit, and the sectoral composition of the sample provided an adequate representation of the entrepreneurial structure in the region.

In the first step, the data underwent a descriptive statistical analysis, during which the averages, standard deviations, and 95% confidence intervals of the variables were calculated. A Kolmogorov-Smirnov test was used to compare the sectoral distribution of the sample and the population. The internal reliability of the measuring devices was assessed using the McDonald-omega indicator, as it provides a more accurate estimate than the traditional Cronbach alpha, especially in cases where the conditions of equal factor loading and uncorrelated errors are not met.

The PLS-SEM method used in the research was used to build route models connecting latent variables (Tenenhaus et al., 2005). The PLS algorithm models the relationship between constructs and their indicators on two levels: the outer model examines the relationship between latent and observed variables (Lohmöller, 1989), while the inner model examines the relationship between latent variables. The method is located within the SEM framework, and due to its component-based nature and flexibility against smaller sample sizes, it is beneficial for small and medium-sized enterprise research. The 200 responses used in this study provided sufficient reliability for model fitting.

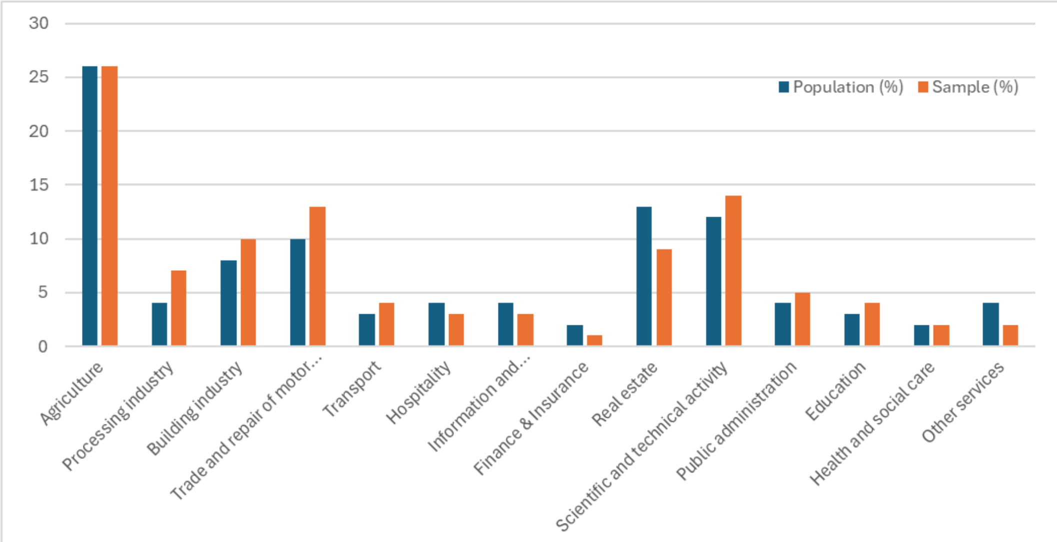
The model development took place in several steps, from the exploration of the constructions to the final model fitting. Initially, exploratory factor analysis (EFA) was conducted using the principal axis factoring method and varimax rotation to identify latent dimensions. This was followed by the reinforcing factor analysis (CFA), the purpose of which was to check the fit of the indicators to the constructs. The final PLS-PM model was set up based on these, and then the relationships between the latent variables were examined (Chin, 1998).

To evaluate the intrinsic quality of the model, the explained variance (R^2) indicators were used. Route coefficients estimated the relationships between the constructs, and their significance was checked using a bootstrap procedure with 500 resamples (Bentler, 1990). Road coefficients can be considered significant if their corresponding t-value exceeds the critical value of 1.96. Discriminative validity was investigated based on the Fornell–Larcker criterion and HTMT indicators (Camară, 2024), while the overall model fit was determined by the Goodness of Fit (GoF) value (Susetyo & Muafi, 2024), which was calculated as the geometric mean of AVE and R^2 (Y. Zhang et al., 2023).

The sectoral deviations of the individual latent variables were tested using the Kruskal–Wallis test (Valaskova et al., 2025). The statistical analyses were performed in the R 4.2.3 language environment using the "plspm" package, and the RStudio (R Core Team, 2023) and Inkscape tools were used for data visualization. Factor analysis and nonparametric tests were performed using the Jamovi 2.4.8 software (Jamovi project, 2023) .

4. Outcomes

In the first step of the study, we compared the background variables of the company population and the sampled companies using statistical analysis, as illustrated in the second figure. The aim of this was to check the representativeness of the sample in relation to the regional entrepreneurial structure. Based on the results of the Kolmogorov–Smirnov experiment, there was no significant difference between the two distributions ($D = 0.143$; $p = 0.983$), which supports that the sample is statistically representative of the target population. Based on the sample, the dominance of the service sector can be observed, which reflects the typical structure of the SME sector.



2. Figure Distribution of sectors: Population sample

Source: Authors' calculation

In the next section, the responses related to digitalisation will be analysed in detail. First, we examined the distribution of the different types of overload, and then we explored their company-wide differences. Subsequently, we presented the mean values and standard deviations of the responses of the test items belonging to the digitization scales, which reflected the characteristics of the observed and actual digitization levels. The results also highlighted discrepancies between companies' responses to self-assessment of technological and human resources as well as infrastructure preparedness.

In order to examine the data more structurally, cluster analysis and FAMD (Factor Analysis of Mixed Data) were used. These analyses have allowed us to group businesses according to digital maturity, taking into account the differences between perceived and actual levels of digitalisation. As a result of the clustering, digitalisation patterns related to different company sizes were also explored, which presented the distribution of digital competencies and the extent of the digitalisation gap broken down by sector.

The reliability and validity of the measurement model were evaluated in several dimensions, taking into account the internal consistency of the constructs, the one-dimensional nature of the factor structure, and the fulfilment of convergent and discriminative validity. To assess internal reliability, the classic Cronbach-alpha and Dillon-Goldstein rho indicators were used, both of which provide information about the homogeneity of the indicators. The obtained values were convincingly above the threshold of 0.7 accepted in social science research, especially in the case of the "Size" and "Perceived2" constructions, where the indicators reached values of 0.815 and 0.882, respectively. The Dillon-Goldstein rho showed values above 0.84 in all cases, which indicates even stronger construction reliability. (Table 1)

1. Table Reliability indicators of the constructions (Cronbach-alpha, rho_A, eigenvalues)

MVs	*C.alpha*	*DG.rho*	*eig.1st*	*eig.2nd*
Real	0.715	0.841	1.921	0.701
Size	0.815	0.889	2.185	0.512
Perceived1	0.752	0.858	2.007	0.551
Perceived2	0.882	0.919	2.967	0.550

Source: Authors' calculation

Based on the principal component analysis, a one-dimensional structure can be identified behind each examined construction. The intrinsic value of the first principal component was significantly higher than one, while the values of the second component fell between 0.512 and 0.701. This supports the fact that indicators are organized around a single latent dimension. In the case of the "real" construction, the eigenvalue is 1.921, and in the case of the "assumed" 2, the value of 2.967 shows robust structural coherence.

The convergence validity was investigated using the Average Variance Extracted (AVE) indicator. For all constructions, the AVE value exceeded the expected limit of 0.5, which suggests that the latent variables are adequately representative of the indicators measuring them. The lowest value was 0.600 ("real") and the highest was 0.731 ("presumed2"). (Table 2)

Table 2. Explained variance and convergent validity of table constructions (AVE, R^2)

Name	*Type*	*R2*	*AVE*
Real	Exogenous	-	0.600
Size	Endogenous	0.264	0.728
Perceived1	Endogenous	0.243	0.633
Perceived2	Endogenous	0.364	0.731

Source: Authors' calculation

The assessment of discriminatory validity was carried out based on the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) indicator. (Table 3, Table 4) In all cases, the Fornell–Larcker matrix proved that the AVE root of a given construct exceeds its correlation with other constructs. The values of the HTMT indicator did not exceed the threshold of 0.9 in any case, and the value between "perceived1" and "perceived2" (0.81) still proved to be acceptable. The confidence interval of the factor loading values was significantly positive in all cases, so the design validity of the model was fulfilled.

Table 3 Discriminatory validity of the schemes — Fornell-Larcker criterion

	Real	*Size*	*Perceived1*	*Perceived2*
Real	0.600			
Size	0.264	0.728		
Perceived1	0.243	0.070	0.633	
Perceived2	0.336	0.195	0.290	0.731

Source: Authors' calculation

Table 4 HTMT (heterotrait–monotrait) ratios for the examination of discriminatory validity

	Real	*Size*	*Perceived1*	*Perceived2*
Real	–	−0.60	−0.60	−0.67
Size		–	0.33	0.45
Perceived1			–	0.81
Perceived1				–

Source: Authors' calculation

Crossloads were also examined to verify the discriminatory validity of the indicators further. Table 5 shows that each indicator shows a higher load for its construct than for any other latent variable, which confirms the distinction between the constructs. The explanation of the variable names in Table 5 is shown in Figure 3.

Table 5: Crossloads of indicators

#	Variable	Latent variable	Real	Size	Perceived1	Perceived2
1	f1	Value	0.825	−0.492	−0.466	−0.564
2	f2	Value	0.768	−0.299	−0.425	−0.384
3	f3	Value	0.728	−0.375	−0.208	−0.357
4	m1	Size	−0.483	0.891	0.246	0.377
5	m2	Size	−0.432	0.816	0.209	0.404
6	m3	Size	−0.392	0.851	0.224	0.346
7	d1	Perc1	−0.488	0.337	0.906	0.561
8	d2	Perc1	−0.247	0.059	0.714	0.339
9	d3	Perc1	−0.367	0.119	0.755	0.312
10	d1	Perc2	−0.510	0.384	0.480	0.898
11	d2	Perc2	−0.573	0.484	0.520	0.915
12	d3	Perc2	−0.448	0.327	0.498	0.864
13	d4	Perc2	−0.434	0.278	0.325	0.733

Source: Authors' calculation

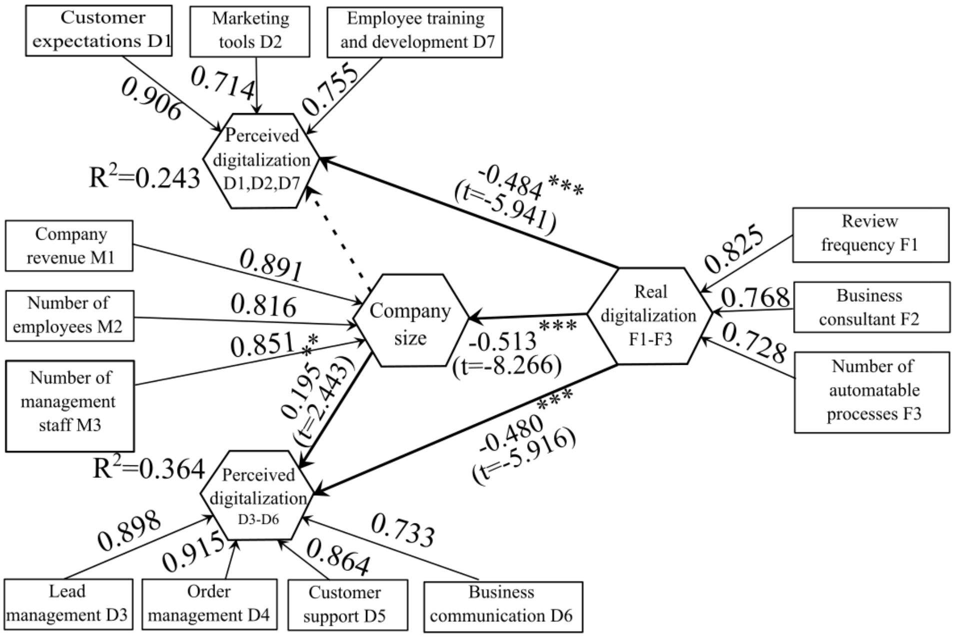
4.1. Structural model: relationships and effects

During the analysis of the structural model, the interpretation of pathway coefficients, the explained variance (R^2) of endogenous constructs, and the evaluation of direct and indirect effects were performed. The fit of the model was measured using the Goodness-of-Fit (GoF) and Standardized Root Mean Squared Residual (SRMR) indicators. The GoF was 0.444, indicating a medium but acceptable model fit, while the SRMR had a perfect fit, as the recommended upper limit is 0.08.

The explained variance of the endogenous variables is as follows: for the "size" construction, $R^2 = 0.264$, based on which the "real" level of digitization explains the size of the enterprise at about 26.4%. In the case of the "perceived1" construct, this value is 0.243, while in the case of the "perceived2" construct, it is 0.364, which highlights the predictive power of the model, especially in the case of self-assessed adaptability.

The assessment of the direct impacts revealed that the "real" level of digitalisation has a negative and significant impact on all endogenous variables, suggesting that more technologically advanced enterprises critically assess their digital maturity. The "size" construction has a significant effect directly only on the "perceived2" construction, while this did not appear in the case of "perceived1".

In the calculation of indirect effects, the mediating role of the "size" construction became significant in the relationship between "real" and "perceived2". This may be particularly important for development policy conclusions, as it suggests that the impact of technological advancement is partly reflected in the self-assessed digital adaptability through the size of the enterprise. (Fig. 3)



3. Figure PLS route model and factor loading
Source: Authors' creation based on the results

One of the most important outputs of the PLS-based structural model is the estimation of path coefficients, which characterize the direct effects between each latent variable. Table 6 shows the estimated directions of action, their corresponding t-values, and p-values. Based on the results, "real" digitalisation has a significant, negative impact on both the perceived adaptability and the perceived digital knowledge, as well as the size of the business. The direct effect of the variable "size" showed only significance on the perceived adaptability. The bootstrap procedure also confirmed the statistical reliability of the model.

6. Table Route coefficients, significance and directions of action of the structural model

Connection	*Estimated impact*	*T-value*	*p-value*	*Significance*
Real → Size	−0.513	8.266	<0.001	< 0.001
Real → Perceived1	−0.484	5.941	<0.001	< 0.001
Real → Perceived2	−0.480	5.916	<0.001	< 0.001
Size → Perceived 1	0.017	0.271	0.393	Ns
Size → Perceived 2	0.195	2.443	0.008	P < 0.01

Source: Authors' calculation

4.2. Exploratory Factor Analysis – Empirical Support of Constructions

Prior to the confirmatory modeling, we performed an Exploratory Factor Analysis (EFA) in order to verify the structure of the measurement model independently and to make sure that the theoretical constructs form clearly distinguishable dimensions. The analysis was carried out using the principal axis factoring method and varimax rotation, which allowed the factor structure behind the items to be separated in an interpretable way. The study included 13 indicators, and the procedure identified four factors that corresponded to the theoretical variables previously defined in the questionnaire.

Based on the indicators of the fit of the model, the data are excellent for factor analysis. The Kaiser–Meyer–Olkin (KMO) value was 0.841, indicating a high sampling conformity, while the Bartlett sphericity test was significant ($\chi^2(78) = 1249$, $p < 0.001$), confirming that the data matrix is not randomly constructed. Additional values indicating the fit of the model – RMSEA = 0.039 and TLI = 0.979 – also strengthened the reliability and stability of the factor structure. The four identified factors reflected well-distinguishable constructions in terms of content. The first factor represented the perceived digital adaptability of the business and included items related to innovation, technological responsiveness, and self-rated digital flexibility. The second factor captured perceived digital knowledge through items aimed at assessing organizational or individual digital competencies. The separation of this dimension from adaptability indicated that respondents have a differentiated understanding of these areas. The third factor described the actual digital infrastructure of businesses, through items focused on software and device usage. The fourth factor represented the size of the company, i.e., the number of employees, sales revenue, and management structure. In all cases, the factor loading values indicated strong associations (between 0.561 and 0.857) with the corresponding indicators.

The results of the exploratory factor analysis empirically supported the conceptual structure of the PLS-SEM model. The constructions were clearly separated from each other, and it was particularly noteworthy that the perceived digitization manifested itself in two separate dimensions (knowledge and adaptation). This suggests that respondents interpret not only technological literacy, but also adaptability to it as an independent aspect. The separation between actual digital capabilities and perceived competencies indicates that respondents consciously distinguish between the technology they possess and their ability to use it effectively. Our results clearly confirm that the discriminatory validity of the scales is met, which is supported not only by the factor structure, but also by the Fornell–Larcker and HTMT indicators of the PLS model.

4.3. Sectoral Differences – Kruskal–Wallis Analysis

In order to explore the differences between the sectors, we used the nonparametric Kruskal–Wallis test, which made it possible to compare the scales of real digital readiness, the two components of perceived digitalisation, and the size of the company. According to the results of the analysis, there was a statistically significant difference between the examined sectors both in terms of actual digitalisation ($\chi^2 = 26.7$; df = 14; $p = 0.021$), company size ($\chi^2 = 36.7$; df = 14; $p < 0.001$) and the first component of perceived digitalisation ($\chi^2 = 36.7$; df = 14; $p < 0.001$). However, there was no significant difference in the second perceived dimension ($\chi^2 = 20.2$; df = 14; $p = 0.125$).

Based on qualitative interpretation, there is a particularly sharp discrepancy between actual and perceived digital readiness in some sectors. Among SMEs in the financial and insurance industries, for example, low real-world digitization values are associated with extremely high perceived levels, indicating a marked perception bias. A similar trend can be identified in the manufacturing industry and in the field of human health services, where the level of technological infrastructure lags behind self-assessed capabilities. The public administration sector, on the other hand, shows the opposite pattern: here, the real digital supply is particularly high, while self-esteem remains at a lower level, which indicates underestimation. In the electricity sector and other services, it can also be observed that technological readiness significantly exceeds the level of perception.

These results suggest that the discrepancy between the perceived and real levels of digitalisation is not only an individual or organizational specificity, but also follows patterns that can be detected along sectoral structures. This discrepancy may have profound implications for development policy interventions, as it suggests that in specific sectors, either in the form of overvaluation or underestimation, a distorted self-image can shape digitization decisions and investment priorities. It is therefore appropriate to take into account sectoral specificities when designing targeted development strategies, especially in cases where there is a significant discrepancy between perceived capabilities and actual infrastructure.

4.4. Evaluation of hypotheses

Based on the results, the following conclusions can be drawn about the hypotheses examined:

- **H1 was confirmed** as there was a statistically significant correlation between the actual level of digitalisation and the digital readiness perceived by enterprises. The direction of the relationship is negative, suggesting that more advanced companies are more critical of their preparedness.
- **H2 was partially confirmed**: larger enterprises assessed their adaptability significantly differently compared to micro-enterprises, but there were no significant differences in all dimensions.
- **H3 confirmed**: the size of the company plays a mediating role in the relationship between the actual level of digitalisation and self-assessed adaptability, which was also supported by the bootstrap process.

5. Discussion and implications

The research aimed to explore the correlation between the real and perceived digital readiness of micro, small, and medium-sized enterprises in Hungary, and how the size of the enterprise influences this relationship. Based on the results of the structural model, it can be concluded that actual digital development has a negative but statistically significant relationship with self-assessed digital competence (KRAJČÍK, 2022). This negative relationship may be surprising at first. Still, it can be interpreted as the fact that more technologically advanced companies are more aware of their shortcomings and are therefore more self-critical in their evaluation.
Based on the examination of the mediating role of size, it can be said that this effect does not prevail in all cases. The size of the enterprise has a significant relationship with perceived adaptability, but it has no significant impact on the perceived digital knowledge dimension. This suggests that organizational capacities, available resources, and internal operational structures have an impact on the perception of adaptability rather than on the perception of overall digital literacy.
Based on the mediation model, real digitalisation also has an impact on perceived preparedness through the size of the company, but this indirect effect is only significant in the case of one of the perceived dimensions. This partial mediation indicates that size alone cannot be considered a full-fledged intermediary factor in the development of digital self-esteem.
Overall, the model showed a good fit (SRMR = 0.038; GoF = 0.444), and the reliability and validity of the constructions have been confirmed. Most of the hypotheses have been confirmed: there is a statistically verifiable relationship between real and perceived digital readiness, and size has also proven to be a meaningful explanatory variable for at least one dimension. The research thus contributes to a deeper understanding of the digital maturity of SMEs and makes it clear that digital self-assessment is not just a technological issue, but is based on a complex interplay of organizational characteristics and perceptions.

5.1. Limitations of research and future research directions

The results of the present research provide valuable insight into the components of the digital maturity of Hungarian micro and small enterprises, but several factors limit generalization. First of all, the scarcity of territorial sampling should be highlighted: the vast majority of respondents come from Hajdú-Bihar County, which may influence the results due to the economic and social characteristics of the region. The geographical concentration of the sample limits the extendability of the conclusions to the national level.
Another limiting factor is the subjective nature of the data used: the study was based on a self-completed questionnaire, which may distort real states at the level of perception and self-reflection. Although some of the hypotheses aim to explore the difference between these perceptions and reality, the self-reported nature of the data can still affect the objectivity of the results.
Another important methodological limitation is that the study is cross-sectional: the data reflect the state of businesses at a given point in time, so they do not provide an opportunity to understand the temporal dynamics of digital development. In future research, it would be

worthwhile to apply a longitudinal approach, which is suitable for a more accurate exploration of the direction, pace, and causal relationships of changes.
In addition, it can be helpful to include qualitative methods – such as interviews and case studies – that can gain a deeper understanding of the motivations and fears of business leaders, as well as the mapping of internal organizational dynamics related to digitalisation. Such approaches can be particularly valuable in further interpreting the differences between perception and reality.

6. Summary

The focus of the study was on the complex examination of the digital readiness of Hungarian micro, small, and medium-sized enterprises. In the course of the research, we analyzed the relationships between real and perceived digital states, as well as the mediating role of company size, using a PLS-SEM model. The analysis confirmed that there is not only a relationship between technological advancement and its self-assessment, but this relationship is not always unequivocally positive. More advanced companies often critically evaluate their digital maturity, while less developed ones sometimes overestimate it.
Organizational size, as a structural factor, partially mediates the relationship between real and perceived digitalisation, but this is only significant in the adaptability dimension. This suggests that perceived digital knowledge is more the result of subjective assessment, while adaptability is more influenced by factors of size, such as access to resources.
Based on the results, it can be said that when planning digital development interventions, the differences between the real and perceived states of enterprises must be taken into account. In the case of micro-enterprises, it is not enough to provide technological support alone: it is also necessary to provide knowledge development, mentoring, and access to resources. The research can contribute to the development of a more conscious, differentiated digitalisation strategy that is better suited to the reality of the Hungarian SME sector.

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