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Exploring the Intersection of Emerging Technologies and Knowledge Management in the context of Ownership Structures

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ABSTRACT

Research background: Each industrial revolution has demanded that people develop specific skills and competencies to stay relevant in the workplace. The first revolution introduced mechanisation, the second emphasised cognitive skills, and Industry 4.0 focuses on digital skills. Over the centuries, the required skills have transitioned from physical to digital. With the growing reliance on information, digital skills have become an essential resource in today's society.

Purpose of the article: The study aims to illustrate the relationship between knowledge management and emerging technologies. It seeks to determine how this relationship varies based on company ownership.

Methods: The main data for the survey was collected through an online questionnaire administered in 2022 using the Lime Survey platform. The survey targeted managers from companies operating in Hungary and received 5,207 valid responses. To test the hypotheses, both univariate and multivariate statistical methods were employed. Descriptive statistics provided an initial overview of the sample, while a multivariate regression model was utilised to address the research question.

Findings & Value added: The results demonstrate that knowledge management projects, alongside technology intensity, significantly influence the adoption of emerging technologies, with a notable impact on financial performance. In terms of technology use and human factors, several efficiency barriers exist, the primary one being the workforce's lack of digital competencies. Foreign ownership positively affects all these aspects. Future research directions include conducting a qualitative survey through semi-structured interviews to validate the large quantitative dataset. Additionally, examining spatial differences, national cultures, and cultural clusters is important, as the results indicate that a company's operational processes, which influence the use of emerging technology in the international arena, are often shaped by the national culture of the parent company.

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INTRODUCTION

Digital innovation is a challenging new direction that permeates all aspects of life, supporting, among others, companies in digital transformation, especially in European countries (Qin et al., 2016). Global companies operate in a highly dynamic environment, driven by technological advances such as artificial intelligence, digitalisation and the increasing impact of emerging technologies (Teece, 2020). Within the European Union (EU) economy, industry stands as the main driver of research and innovation (Blanchet & Rinn 2016). Hungary is positioned as one of the most industrialised countries in the EU, with industry accounting for 23.2% of GDP (KSH, 2022) but falls short of the EU average in terms of digital technology indicators such as digital manufacturing processes, automation and the share of digitally skilled workforce (Nagy et al., 2018).

Digital innovation can be broadly defined as "the creation of (and consequent change in) a market supply, business process or model resulting from the use of digital technology" (Nambisan et al., 2017:224). For industrial organisations, launching and implementing digital innovation is often extremely difficult, as it requires fundamental changes in their operations as well as a strategic and organisational transformation that alters the value creation logic of companies (Singh et al., 2020). Over the past decade, organisations have been affected not only by disruptive innovation driven by technological advances, accelerated by digitalisation and artificial intelligence (García-Villaverde et al., 2018), but also by rapidly growing, evolving complex emerging market players challenging the dominance of the West (Li et al., 2019). Chatbots, artificial intelligence, machine learning, intelligent robotics, big data and the Internet of Things are just a few examples of the rapidly evolving technological landscape. Simultaneously, individuals and organisations are producing and accessing data that can lead to more valuable information and knowledge.

Adomako (2021) describes the dynamic environment as "characterised by frequent changes that lead to unpredictability and a high degree of uncertainty". In this highly dynamic environment, characterised by volatility, uncertainty (Adomako, 2021), complexity (D'Innocenzo et al., 2016) and ambiguity (Hansen et al., 2019) (Pereira & Bamel, 2021) (referred to as a VUCA world), unpredictable, multi-level crisis events allow very little time to plan possible solutions and next steps. At the same time, more and more organisations are recognising that effective knowledge management is a pivotal driver of success, helping them to be resilient and ready for change, with a knowledge management strategy that incorporates the three main pillars of business process management: people, process and technology.

With the advent of not only human-human but also human-machine interactions, the rise of human and machine intelligence could revolutionise knowledge management. The role of digital technologies is not to replace people, but to enable people and technology to work together. Humans are capable of performing tasks that machines cannot learn or automate, and this fact requires the development or reinforcement of skills that cannot be transferred to machines through machine learning or artificial intelligence (Mortensen, 2017). The worker in the digital age must have technological, methodological, social, and personal competences that need to be continuously developed (Agolla, 2018; Hargitai & Bencsik, 2023).

THEORETICAL BACKGROUND

Knowledge management

Academic literature points out the prominent role of knowledge management and knowledge transfer through the transformation of explicit and tacit knowledge (Nonaka & Takeuchi, 1995; Astorga-Vargas et al., 2017). Polányi's philosophical approach is the basis of the concept of knowledge and knowledge management, regarding his statement that a distinction should be made between explicit and tacit knowledge. Explicit knowledge encompasses knowledge sets that can be captured, collected, edited, easily transferred, and learned. Tacit knowledge, on the other hand, can be described as "knowing more than we can say". Tacit knowledge is an intellectual thought, a personal opinion, or intuition that is personal, subjective and experiential and is closely related to the knowledge holder. Polányi compared human knowledge to an iceberg, with the part above the water level being explicit and the rest tacit knowledge (Polányi, 1966).

Following in the footsteps of Polányi, Nonaka and Takeuchi (1995) developed a knowledge conversion model (one of the most popular to date) based on tacit and explicit categories of knowledge, which became famous as the SECI model. In their model, they distinguish between four types of individual knowledge transfer: socialisation: tacit knowledge —› tacit knowledge; externalisation: tacit knowledge —› explicit knowledge; combination: explicit knowledge —› explicit knowledge; internalisation: explicit knowledge —› tacit knowledge. The process always starts anew, as the creation of knowledge is a series of continuous and dynamic interactions between the four elements. Knowledge management plays a significant role in the success of an organisation's activities and strategies (Castrogiovanni et al., 2016) and can be defined as processes that support the it in the creation, acquisition, discovery, organisation, use and dissemination of knowledge within the organisation (Al-Shanti, 2017). The four types of knowledge management components are defined in recent studies as knowledge generation, knowledge codification, knowledge transfer/sharing and knowledge utilisation for the sustainable success of businesses (Obermayer & Tóth, 2020; Zaim et al. 2019).

Knowledge management strategy

Knowledge management can be viewed from a strategic perspective and the term knowledge management strategy was coined as early as the late 1990s to describe a set of objectives for managing knowledge within a company and the methods for achieving them (Andriani et al., 2019). The development of a knowledge management strategy is essential for the functioning of organisations, as the organisational knowledge accumulated during the course of their activities must be collected, applied and transferred. In principle, companies have the option to choose between three strategic approaches, the systematic - organisation-centred strategy, the relational - product-centred strategy and the environmental - customer-centred strategy (Hemel & Rademakers, 2016). The systematic strategy is characterised by the fact that knowledge is stored in databases and made available to stakeholders from there. Its primary task is to codify knowledge, document it and develop various methodologies (" push"). The focus is on explicit knowledge, with an emphasis on efficiency. As for the relational strategy, computing is employed to support communication between individuals. The focus is on tacit knowledge, the emphasis is on innovation. Knowledge is also seen as an asset but tends to be invested in custom solutions. It seeks to develop systems to support the sharing of tacit knowledge ("push-pull") (De Silva et al., 2023).

Knowledge management projects

An important aim of knowledge management projects in companies is to capture, record and share the knowledge their people possess, i.e. to transform individual knowledge into organisational knowledge.

Knowledge management projects can be broadly divided into three categories: those that seek to create a knowledge base, those that seek to improve access to information and knowledge (knowledge transfer), those that seek to improve the culture and environment surrounding knowledge (Breznik, 2018), and those that seek to measure the knowledge assets, which are increasingly important today. A knowledge base project aims to embed knowledge in documents and then place it in knowledge repositories or knowledge bases where it can be easily inventoried and retrieved. A project to improve knowledge sharing and access aims to make knowledge accessible and facilitate its transfer between individuals. The knowledge sharing culture support programme aims to create a supportive environment in which companies can shape employee behaviour towards knowledge. In this environment, knowledge workers feel comfortable, have the opportunity to learn, to work effectively and they can be creative and innovative.

Trust is the key to building a knowledge-sharing culture. An organisational culture based on trust strengthens cohesion among employees, supports the success of knowledge sharing, leads to more efficient work and honest communication (Bencsik & Juhász 2018). The knowledge asset measurement programme aims to measure the value of the knowledge assets in the company.

Emerging technologies

Technology can provide one of the most effective answers to today's challenges. Technology must be used to support your business to change and grow through innovative solutions. Rotolo et al. (2015:4) identified five characteristics of emerging technologies: radical novelty, relatively rapid growth, coherence, high impact, and uncertainty and ambiguity, and defined emerging technologies as „a relatively fast-growing and radically novel technology, characterised by a degree of coherence over time, that can have a significant impact on socio-economic domain(s). However, its most significant impact is yet to come, and therefore its emergence phase is still somewhat uncertain and ambiguous".

Emerging technologies are transforming work in unexpected ways, both at an individual and organisational level. According to Razkenari et al. (2019), emerging technologies can bring a number of benefits to the industrialised construction industry, including improved communication with team members, improved information sharing and accessibility between partner companies, and improved quality of work.

The concept of digital transformation can be described as a change in the business models of organisations to use digital technologies such as the Internet of Things (IoT), artificial intelligence, machine learning, augmented reality (AR) in order to build innovation in products, services and processes (Machado et al., 2021) Digital transformation is "a process that aims to improve an entity by inducing significant changes in its properties through a combination of information, computing, communication and social technologies" (Vial, 2019:121). Digital transformation consists of three main phases (Verhoef et al., 2019). In fact, digital transformation itself develops as the final stage of the process, which involves the systemic and extensive use of digital technologies. The emerging technologies that are the focus of our research are presented in Table 1.

Both national and international literature points to the importance of Industry 4.0 and emerging technologies (Obermayer et al., 2022; Shahi & Sinha, 2021; Teece, 2020). The results of empirical research highlight differences in the way a firm's technology orientation is influenced by ownership composition (Skare & Soriano, 2021), firm size (Horváth & Szabó, 2019), management and ownership attitudes (Obermayer et al., 2021), country-specific factors or the age of managers and owners (Éltető & Sass, 2021). However, the use of emerging technologies is not only a technological but also a socio-economic phenomenon, affecting all industries and having a significant impact. Domestic studies have, for example, addressed the issue of the spatial structure of firms (location of the firm's operations or type of company location) (Kiss & Nedelka, 2020; Szabó & Hortoványi, 2021).

This paper presents the results of studies on the technological dimension of Industry 4.0 and the ownership composition (foreign ownership).

Emerging technologies in Europe and in our country

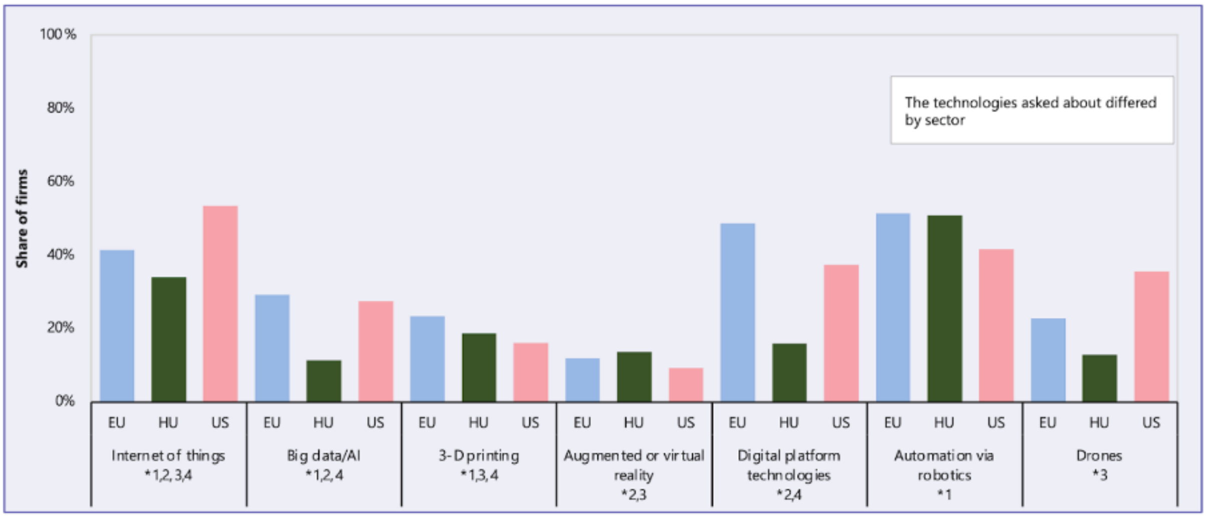
The EIB Group's Investment and Investment Finance Survey is a unique annual survey of around 13,500 firms in all EU Member States and a sample of US firms, which serves as a benchmark. The report confirms that firms with high value-added activities are more likely to adopt digital technologies. The share of firms adopting technologies is higher in innovative sectors, such as high-tech-intensive manufacturing and high-tech knowledge-intensive services. Hungary is ranked among the medium countries in the EIBIS Digitalisation Index. The digital switchover rate in Hungary is below the EU average in all sectors. More than half of enterprises (53%) use at least one advanced digital technology, but this is much

Table 1: Characteristics of the emerging technologies studied in the research

Emerging technology	Feature
Artificial intelligence	There are two types of artificial intelligence: weak (or narrow) and strong. Narrow AI describes computer systems that are skilled at performing certain tasks (e.g. Apple's virtual assistant Siri, which interprets voice commands). Strong AI, also known as artificial general intelligence (AGI), is a hypothetical type of AI that can match or exceed human-level intelligence and apply its problem-solving ability to any type of question (Atkinson 2018).
Augmented reality	It is the addition of virtual objects to a person's environment. Natural perception is built up with three-dimensional elements, where a person is constantly aware of his or her own physical environment, but additional elements (texts, symbols, images, videos) appear in his or her field of vision (PWC 2016).
3D printing	Based on digital models, it creates three-dimensional objects by layering or "printing" materials on top of each other using innovative inks, including plastic, glass or wood (PWC 2016).
Chatbot	According to the dictionary, a chatbot is "a computer program designed to simulate a conversation with human users over the Internet". A chatbot (robot) is software running on messaging platforms that is capable of simulating or imitating human conversation (Adamopoulou, Moussiades 2020).
Ticketing system	User-submitted problems form a ticket that is collected and tracked by the IT Helpdesk. A web-based system is an application that is built as a ticketing tool and can be used by the IT department as a communication channel with users (Rachmawati et al. 2019).
Collaborative technologies	According to a study by Shamsuzzoha et al. (2016), collaborative infrastructure facilitates the efficient integration of internal and external manufacturing resources and supports business collaboration. These technologies reduce the cost and time associated with facilitating teamwork, from assigning roles and responsibilities to transmitting documents on site to checking and approving project deliverables.
Content-based recommendation system	Content-based recommendation systems focus on recommending items that contain similar features to other items that the same user has liked in the past. The process involves comparing the attributes of a user's profile, which stores preferences, with the attributes of a content object in order to recommend new items of interest to the user (Javed et al. 2021).
Management Information System (MIS)	MIS is a set of systems and procedures that collect data from different sources, compile them and present them in a readable format. Today's management information systems rely on technology to compile and present data.
Fraud detection software	It is used to detect illegal and high-risk transactions carried out online. These tools continuously monitor user behaviour and calculate risk figures to identify potentially fraudulent purchases, transactions or accesses.
Customer relationship management (CRM)	CRM is an information industry term for methodologies, software and, more generally, Internet capabilities that support an organisation in managing customer relationships in an organised way (Buttle, Maklan 2019).
Biometric authentication	Security procedures that verify the user's identity using unique biological characteristics such as retina, iris, voice, facial images and fingerprints.
Technologies supporting HR processes (e-HR)	Technology has given HR professionals tools that reduce the time they spend on administrative tasks and allow them to focus on issues that require more practical attention (Mizrak, 2023).
Robotic Process Automation (RPA)	A software technology that facilitates the construction, deployment and management of software robots that interact with digital systems and software to mimic human actions.
Business intelligence software	A set of tools to extract, analyse and transform data into useful business insights. Examples of business intelligence tools include data visualisation, data warehousing, dashboards and reporting.

Source: own research

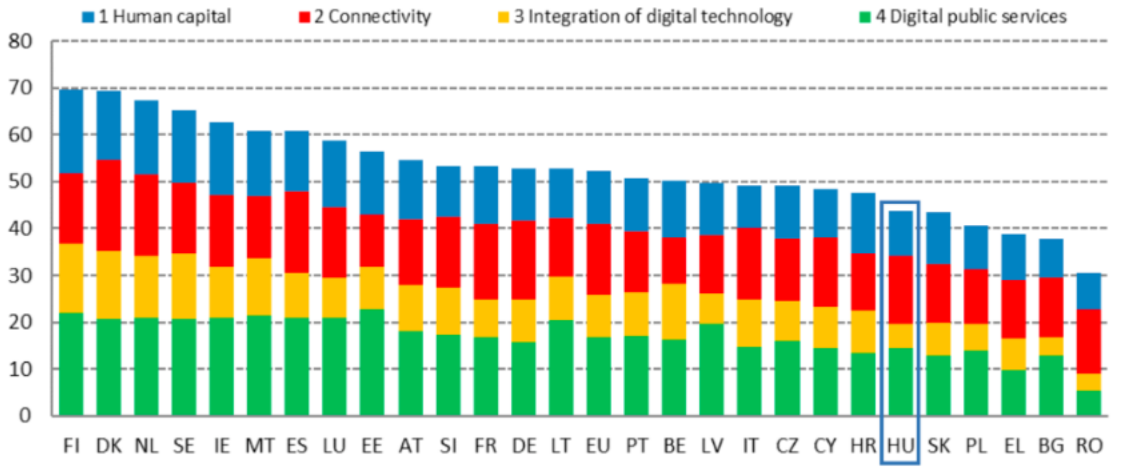
Figure 1: Digital technology use (%) in Hungary



Legend: Sector: 1 = manufacturing (145) 2 = services (120) 3 = construction (113), 4 = infrastructure (103)

Source: EIBIS 2022:9

Figure 2: The DESI indicator in the European Union countries



Source: European Commission, 2022

lower than the EU average (69%). Compared to the EU average, Hungarian enterprises use a number of technologies to a lesser extent (Fig. 1.) The share of Hungarian firms investing in innovation (27% versus 34%) and the share of firms classified as active innovators (11% versus 18%) are both lower than the EU average (EIBIS, 2022).

The DESI 2022 indicator measuring the development of the digital economy and society ranks Hungary 22nd among the 27 EU Member States (Fig. 2). The country's progress over the last few years has been broadly in line with the EU average. Although progress was made in the digitisation of businesses in 2021, the majority of Hungarian businesses fail to exploit the opportunities offered by digital technologies. 21% of enterprises use enterprise resource planning software to share information electronically (EU 38%), and 13% use social media tools (EU 29%) or e-invoicing (EU 32%). The situation is similar for advanced technologies: Hungary is also well below the EU average for artificial intelligence, cloud services and big data. The take-up of these services ranged between 3% and 21%, against the Digital Decade 2030 target of 75%. SMEs require special policy attention, as only 34% of them have at least a basic digital intensity (EU average: 55%), compared to the Digital Decade target of at least 90% (European Commission, 2022).

Another major problem, according to the DESI 2022 indicator, is that only 49% of Hungarians have at least basic digital skills, compared to the EU average of 54% and the Digital Decade 2030 target of 80% (European Commission, 2022).

RESEARCH OBJECTIVE, METHODOLOGY AND DATA

Theoretical model and hypotheses

Research questions drawn from the literature reviewed above (Skare & Soriano, 2021; Obermayer et. al., 2021, Szabó & Hortoványi, 2021; Obermayer, et al., 2022) and the authors' own experience:

- RQ1: Can a significant difference be detected in the relationship between ownership, the level of knowledge management strategy/project implementation and the technological intensity of production and operations?

- RQ2: What factors are most influential in the use of emerging technologies in foreign and domestically owned firms?

The empirical study aims to build on the theoretical foundations and the research question to investigate the factors influencing the use of emerging technologies in the context of ownership (purely domestic or foreign-owned enterprises). SPSS Statistics 22 software was used for the analyses. The operationalisation of the model constructs is summarised in table 2, as the conceptualisation has been included in the theoretical summary.

Table 2: Operationalisation of model constructs

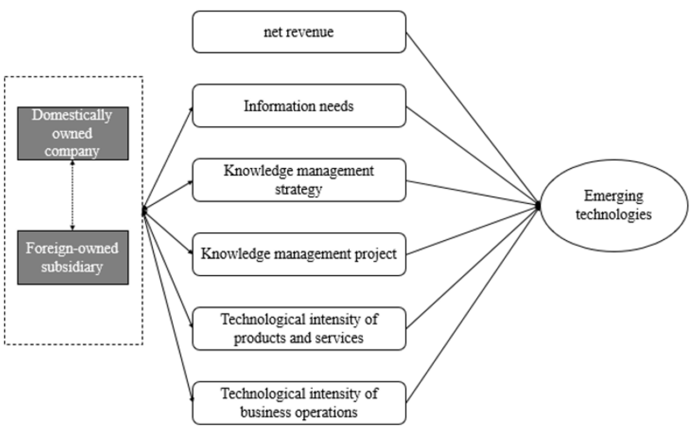
Model construction	Operationalisation
Emerging technology	In the questionnaire, the use of emerging technologies, as represented in the theoretical summary, was examined as a dummy variable from which a continuous variable was transformed as a frequency variable.
Knowledge management project	The variable measured the depth of use of the knowledge management project on a 5-point Likert scale.
Knowledge management strategy	The depth of the existence of a knowledge management strategy was measured by the variable on a 4-point Likert scale.
Technology intensity	The technological intensity of products and services and of the company's operational processes were measured by the two variables on a 4-point Likert scale.

Source: own research

Both domestic and international literature points to the importance of Industry 4.0 and emerging technologies in particular (Obermayer et al., 2022) and several empirical studies point to the difference that the technological orientation of a firm is strongly influenced by its ownership composition. Both managerial and ownership attitudes are determinants, especially in small and medium enterprises (Obermayer et al., 2021). The present research measured the abundance of emerging technologies, which were identified as influenced by the degree of implementation of knowledge management strategy and projects, while technology intensity was scaled into two parts: product and services and company operational processes. The analysis is based on the factors that influence the use of emerging technology and whether there is a difference in the aspect of ownership (Fig. 3). Based on the relational framework of the model, the following hypotheses were formulated:

- H1a: The level of implementation of knowledge management strategy/projects differs significantly in relation to ownership.
- H1b: The technological intensity of production and operational processes is significantly different in relation to ownership.
- H2a: In addition to sales, the technological intensity determines the use of emerging technologies for a given strategy.
- H2b: The impact of factors influencing the use of emerging technologies differs across ownership.

Figure 3: The research model



Source: own research

Data collection and methodology

The primary source of data for the survey was an online questionnaire, administered in 2022 via the Lime Survey platform. Respondents completed the survey anonymously, with an average response time of approximately 10-15 minutes. The target group comprised managers of businesses operating in Hungary, who were reached through the Orbis database (which contains business data of nearly 400 million companies and legal entities worldwide). The screening process considered factors, such as the location (the country of the survey), the size of the company and the sector to which the company belongs based on its main activity. The sampling technique used was stratified sampling. This involved the formation of strata based on the characteristics mentioned above, from which the sample was selected separately. The filtering was done using the Orbis database, ensuring that all relevant aspects were taken into account in the sampling for the study.

As a result, more than 40,000 companies were selected as potential respondents. In addition to basic organisational information, the questionnaire explored the context of knowledge management and emerging technologies. Univariate and multivariate statistical methods were used to test the hypotheses. Descriptive statistics serve as the primary situational representation of the sample, while a multivariate regression model was used to answer the research question. The statistical method examines the influence of the independent variables included in the model on the dependent variable "Emerging technologies". As a method for regression models, the backward procedure is justified, as it first incorporates all variables into the model and then eliminates them one by one in such a way that the explanatory power of the model does not change significantly (Abebe 2024). The input variables of the regression model were tested for the relationship of ownership using an independent samples t-test.

Sample characteristics

The survey resulted in an evaluable sample of 5207 respondents. To avoid data bias, the questionnaire also provided a "don't know" response option for Likert-type questions, which were treated as missing values in the analysis. This allowed for a net sample size of 2709 respondents after data cleaning. These respondents provided complete responses for all variables used in multivariate statistical analyses. Looking at the data from the Central Statistical Office (CSO, 2022), the sample can be considered as having limited representativeness both in terms of type of activity and number of employees. The general characteristics of the sample in relation to the research questions and hypotheses are presented in the breakdown of ownership (foreign versus 100% domestic) of Hungarian enterprises (table 3). The descriptive statistics obtained show that the respondents of the domestically owned enterprises (n1= 2414) were typically top-level managers (75%), while the proportion was 38% for foreign-owned (n2= 295) organisations. According to the SME classification (based on number of employees and turnover) published by the European Union, almost half of the subsidiaries in the sample (45.76%) are large enterprises, while 80.45% of the domestically owned firms fall into the category of micro-enterprises. From a sectoral point of view, the tertiary sector accounted for almost 80% of the sample, while the extractive (primary) sector accounted for only 2.6%.

Table 3: Demographic characteristics of the sample

Category	Variables	100% domestically owned enterprise	Foreign-owned subsidiary
Position	intellectual worker	90 (30.5%)	313 (13%)
	middle manager	93 (31.5%)	291 (12%)
	senior manager	112 (38%)	1809 (75%)
Company size	micro-enterprise	72 (24.44%)	1942 (80.44%)
	small enterprise	40 (13.55%)	172 (7.12%)
	medium enterprise	48 (16.27%)	131 (5.42%)
	large company	135 (45.76%)	169 (7%)
Sector	primary	10 (3.39%)	61 (2.52%)
	secondary	68 (23.05%)	378 (15.65%)
	tertiary	210 (71.18%)	1951 (80.82%)

Source: own research

RESULTS

An important aspect of the analysis of quantitative data is the statistical evidence of differences in ownership, and the analysis and interpretation of the data, which this chapter aims to present. In the first part of the analysis, the ownership differences of the predictor variables were explored, which contributes to answering the first research question. To check the identity of the variances of the multivariate variances, the Levene test is to be used, if homoscedasticity is not met the Welch test can be used instead of the two-sample t-test, as it tests the same null hypothesis and does not require the identity of the variances (Cleophas & Zwinderman, 2016). Table 4 shows that for all variables under investigation, we see a significant difference in whether the firm is a domestically owned firm or a subsidiary of a foreign firm. All variables except the knowledge management project were measured on a 4-point Likert scale. The largest average difference was for knowledge management strategy (MDstrategy = 1.695) and project (MDproject = 1.479).

It can be seen (in table 4) that foreign-owned enterprises operating as subsidiaries give a high priority to knowledge management; hence the marked average difference of more than one, which can, in fact, be interpreted as a background variable for financial success. This is confirmed by a stronger than medium correlation with turnover ($r = 0.656$, significance < 0.05). The difference in the intensity of technology within the company's operational processes and products is significantly smaller, suggesting that the use of emerging technologies is necessary for the companies and that managers are aware of its importance. This result is supported by the fact that the average value for the technological intensity of products and services for the domestically owned companies is 2.8, while the average value for subsidiaries is 3.2, which gives the smallest average deviation (MDproducts and services = 0.452). In the light of the above, the first hypothesis that the level of implementation of knowledge management projects and strategies and the technological intensity of production and operational processes in relation to ownership differ significantly, is accepted.

The second research question requires linear regression analysis, which has several conditions. The linearity was checked by a simple point cloud plot and the homoscedasticity (constant variance) criterion was violated as described above, but the multicollinearity condition was met as the correlation of the predictor variables varies between [0.116 - 0.565] with no strong relationship. The level of the VIF indicator associated with collinearity cannot exceed 5, a check for this can be obtained by running

Table 4: Differences in factors affecting emerging technologies from an ownership perspective

Predictor variables	foreign ownership: 100% domestic		Levene statistics		T-test results		
	Average1	Average2	T-test	sign	t	sign	Mean deviaton (MD)
Knowledge management strategy	3.42	1.76	14.462	<0.05	11.985	<0.05	1.695
Knowledge management project	4.27	2.79	285.434	<0.05	13.96	<0.05	1.479
Net revenue	2.53	1.27	356.358	<0.05	18.099	<0.05	1.26
Technological intensity of products and services	3.28	2.83	13.059	<0.05	8.011	<0.05	0.452
Technological intensity of business operations	3.12	2.57	14.57	<0.05	9.521	<0.05	0.549
Information needs	3.09	2.73	49.975	<0.05	6.615	<0.05	0.357

Source: own research

Table 5: Results of the regression model from an ownership perspective

Ownership	Predictor variables	Standardised coefficients Beta	t	sign	Collinearity	
					Tole-rance	VIF indi-cator
Foreign-owned subsidiary	Dependent variable: number of emerging technologies used (R^2 = 0,363)					
	Net revenue	0,114	1,607	<0,05	0,9	1,11
	Technological intensity of business ope-rating processes	0,29	3,887	<0,05	0,81	1,233
	Comprehensive knowledge management strategy	0,206	2,863	<0,05	0,87	1,148
Domestically owned company	Dependent variable: number of emerging technologies used (R^2 = 0.389)					
	Net revenue	0,108	4,47	<0,05	0,95	1,052
	Technological intensity of products and services	0,164	5,148	<0,05	0,54	1,841
	Technological intensity of business ope-rating processes	0,061	1,84	<0,05	0,5	1,981
	With a comprehensive knowledge mana-gement strategy	0,081	2,51	<0,05	0,53	1,868
	Knowledge management project	0,251	7,705	<0,05	0,52	1,91

Source: own research

the regression model. The Durbin-Watson test is d = 1.928 and 1.980 respectively, so for variables explaining at 5% significance level dU = 1.856 < 1.980, null hypothesis is accepted so the error terms are not considered autocorrelated.

The adjusted R2 is 0.363 for foreign-owned subsidiaries and 0.389 for domestically-owned firms, indicating that almost 40% of the variables included in the model explain the number of emerging technologies used. The results for the significant predictor variables that make up the model are shown in table 5. Among foreign-owned subsidiaries, the technological intensity of the operating processes has the largest effect on the number of technologies used ($\beta_{külföldi}$=0.290). In the context of the sample characteristics, it can be seen that the organisational tasks of the company may result in a significant emphasis on processes from the perspective of technology use, as the proven business model has to be operated across borders. In contrast, revenue is the least significant variable ($\beta_{külföldi}$=0.114), which also implies that the use of emerging technologies is primarily a non-material issue.

For domestically owned firms, several explanatory variables show a significant effect, but here (probably due to the larger mass of smaller firms) knowledge management projects have the largest effect (β_{hazai}=0.251) and the technological intensity of products and services (β_{hazai}=0.164) have the largest effect. Revenue is not the most significant variable here either (β_{hazai}=0.108). H2a is only partially acceptable as some variables are dropped from the hypothesised model, but H2b is acceptable as some different predictor variables appear in the two segments, and with significantly different weights.

DISCUSSION

The aim of the research is to illustrate the relationship between knowledge management and emerging technologies. Moreover, the purpose was to answer the research questions (RQ1; RQ2) and to verify the hypotheses (H1; H2). The study seeks to determine how the relationship varies based on company ownership.The answers to the research questions based on the analyses of the questionnaire with 2709 respondents (descriptive statistics and regression model) are explained in the previous chapter. These can be briefly summarised as follows.

To answer the first research question (RQ1) the spatial distribution between the level of implementation of knowledge management strategies and projects and the technological intensity of production and operational processes, i.e. the differences in the practices of domestic and international firms, was analysed and a significant difference was found. For the second one (RQ2) the factors that most influence the use of emerging technologies, also spatially distributed, were identified. The results lead to the conclusion that for the companies studied, the attitude towards knowledge management of all organisations, regardless of size and spatial, i.e. ownership, is more likely to influence the use of emerging technologies than financial considerations or even the pressure of the international parent company (Obermayer et al., 2022).

Similar to the result of Horváth & Szabó (2019), our research identified (H1a) that the level of implementation of knowledge management projects and strategies and the technological intensity of production and operational processes (H1b) in relation to ownership differ significantly. According to the participants, our findings are also consistent with Obermayer et al. (2022), in foreign-owned subsidiaries and also in domestically-owned companies, revenue is is not the most significant variable, which indicates that the use of emerging technologies is primarily a non-financial issue (H2a). H2a can only be partially accepted, since the technological intensity of products and services of foreign-owned subsidiaries does not significantly affect the number of emerging technologies used. Among foreign-owned subsidiaries, the technological intensity of the operating processes has the largest effect, while among domestically-owned companies, knowledge management projects and the technological intensity of products and services have the largest effect. Our results indicated in parallel with Skare & Soriano (2021), regarding the factors influencing the use of emerging technologies as some different predictor variables appear in the two segments with significantly different weights, so the H2b is acceptable.

CONCLUSION

Our results provide valuable insights for business decision-makers on where to allocate money when allocating scarce resources. It can be seen that, for domestic companies, the technological intensity of products and services is more likely to determine the use of assets and the launch of knowledge management projects, while for international companies it is the technological intensity of the company's operational processes and the development of knowledge management strategies. The latter emerges as a good practice for domestic companies to consider knowledge management as a strategic objective. From a knowledge management perspective, one of the biggest challenges facing society is the spread of the use of emerging technologies and thus the growth of virtual workplaces.

However, this requires a workforce with high levels of digital competence and effective knowledge sharing. In the future, knowledge management will no longer be a human task but will be shared between humans and technology. The basis for effective knowledge management lies in human-technology collaboration, the appropriate use of digital technologies and people's attitudes.

Synergies between knowledge management and emerging technologies promise to shape how organisations create value from their intellectual assets in the future. At the same time, it also poses challenges in terms of data management, ethical considerations and the need for a workforce skilled in both technology and knowledge management practices. The pandemic has accelerated the spread of emerging technologies, with the overnight shift to remote working. In the future, workers will need the right digital technologies to acquire and transfer knowledge and information. Companies need to provide these tools not only to support remote workers in virtual communication and collaboration, but also to prepare for another unexpected event, even a new pandemic. Today, no one disputes that one of the key success factors for organisations is the ability to effectively manage (share, store, use) knowledge as it is constantly renewed. Prioritising knowledge sharing and providing the necessary digital technologies and workforce with digital competences is essential for the long-term survival of organisations.

The future direction of the research is, on the one hand, to conduct a qualitative survey (semi-structured interviews), which will provide an opportunity to validate the large sample of quantitative data. On the other hand, as the results show that corporate operational processes are more likely to determine the use of emerging technology in the international arena, and this may depend to a large extent on the national culture of the parent company, we can also look at spatial differences in terms of national cultures, culture clusters. The question may arise whether there are similarities between post-socialist countries and how much differences can be observed between members of the Anglo-Saxon or even Germanic culture cluster (Hungary belongs to the latter cluster).

A limitation of the research is that the questionnaire used in the quantitative survey is essentially a sliding scale questionnaire based on self-reporting, and thus may be biassed in terms of results. This limitation should be overcome by continuing the research in a qualitative direction.

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