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Structural Model of Technological Collaboration within a Manufacturing Cluster

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Abstract
The aim of this study is to examine the collaboration among members of a business cluster in the field of technology management, specifically focusing on the Metal Processing Cluster operating in Poland. Utilizing survey data, a structural model is developed through the Partial Least Squares Structural Equation Modelling technique. The resulting statistically valid model elucidates several significant relationships that are crucial for fostering collaboration within a business cluster, while simultaneously affirming the advantages associated with membership in such an organizational structure. Participation in a cluster has the potential to expedite information acquisition, cultivate valuable new knowledge within firms, and yield both operational and strategic benefits. Although knowledge that facilitates and supports innovation is deemed essential for maximizing the advantages of cluster participation, a significant number of surveyed cluster companies have yet to implement such knowledge, suggesting the existence of untapped opportunities for further benefits among members.

Keywords
cluster, technology, collaboration, manufacturing, PLS-SEM.

Introduction

An important issue in the product innovation and competitiveness area is the technological changes, which can impact not only individual companies but also entire industries in various ways. Technological change is a major focus of technology management (TM) research. While a substantial amount of information on this topic is available in the literature concerning business organizations, there is a notable paucity of knowledge regarding interorganizational collaboration within the realm of technology management (Krawczyk-Dembicka, 2017). One of the pioneers in TM research, Gregory, contributed significantly to the understanding of the general framework of the TM process (Gregory, 1995). Subsequent scholars have identified several valuable concepts that enhance his foundational work (Cetindamar et al., 2016a). However, the existing literature has predominantly concentrated on individual companies or specific industries, leaving the exploration of multi-actor collaboration largely unaddressed. Consequently, it is posited that the most suitable context for investigating this issue would be the structure of a business cluster, which fundamentally embodies interorganizational collaboration across various critical business domains.

A business cluster is defined as a collective of interconnected research and development units, institutions within the business environment, and companies that operate within the same industry sector and specific geographical regions. All entities affiliated with a cluster share common objectives aimed at deriving specific advantages from their participation in the cluster (Porter, 2000; Awad & Amro, 2017). Among the various benefits that companies engaged in a cluster structure may experience, the literature highlights advantages such as reduced operational costs, enhanced revenues and profits, and an overall increase in the competitiveness of both the firms and the surrounding region (Hsu et al., 2013). Furthermore, research indicates that firms benefit from technological advancements, heightened innovation, and improved research and development capabilities, which include the sharing of information, resources, and knowledge (Anić et al., 2022; Awad & Amro, 2017; Hsu et al., 2013; Porter, 1998). The configuration of a business cluster is distinctive due to the simultaneous presence

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of collaboration and competition among the participating partners, which represents a unique model of collaboration (Grangsjo, 2003; Nie et al., 2020).

The aim of this study is to conduct a thorough investigation of the internal collaboration with regard to TM among members of the business cluster of metal processing companies. This research identifies the factors that influence TM in these companies, as well as the advantages gained from their participation in the cluster. Additionally, common practices employed by the companies in the realm of TM were delineated. The data collected facilitated the development of a model illustrating the impact of business cluster membership on the TM domain among the participating companies.

TM and business clustering

A pioneer in TM research was Gregory, whose model comprises five primary TM processes (named often as TM stages): identification, selection, acquisition, exploitation, and protection (Gregory, 1995). Subsequent researchers have expanded upon his framework by incorporating considerations related to knowledge, technology development, organizational levels, firm strategy, market mechanisms, and technology withdrawal (Phaal et al., 2004; Cetindamar et al., 2016b; Skilbeck & Cruickshank, 1997; Sumanth & Sumanth, 1996; Levin & Barnard, 2008). It is important to note that technologies acquired by companies often necessitate customization to address the specific needs of the organization. Furthermore, when technologies are developed from scratch, a comprehensive analysis of their functionality and the formulation of specific technological assumptions are essential. These tasks fall within the domain of TM and pose significant challenges for many organizations, as evidenced by numerous academic studies (Lee & Kang, 2018).

Nowadays, technology is regarded as the primary driving force behind organizational success. Consequently, effective TM is perceived as a vital tool for creating customer value, which simultaneously fosters a competitive advantage (Bandarian, 2020). Thus, it can be concluded that TM plays a crucial role in economic development (Yubo et al., 2023). An in-depth study conducted by Urban and Krawczyk-Dembicka (2020) revealed that TM in metal processing manufacturing firms is grounded in technological principles, modular acquisition, technology adaptation, and commissioning. These activities are interconnected with economic evaluation, and each step comprises a series of tasks that demand significant time and effort from employees. Furthermore, their findings indicate that certain typical activities outlined in the literature on the TM concept, such as knowledge protection measures, may not be implemented at all be business players, despite the fact that knowledge itself is essential in the course of TM process.

Cetindamar et al. (2016a) emphasize that technological competence and knowledge-sharing skills are crucial at every stage of TM. They also highlight the significance of the learning process itself, which encompasses technological activities that occur both within and outside the firm. This learning process serves as a foundation for establishing collaboration with other entities for knowledge sharing and technology development. Furthermore, they point out that the execution of individual technology management activities is influenced by the competence of managers, which can determine their inclusion or exclusion within a given company. It is important to note that many TM activities are integrated by companies into other business processes (Phaal et al., 2001), such as those related to supply chain management or new product development. This integration often complicates the clear definition of a technology management framework. To effectively incorporate technology into the business, it is essential to leverage acquired knowledge and experience.

Knowledge, both tacit and explicit, is a crucial factor in the success of any organization and plays a significant role in gaining a competitive advantage for the company (Qandah et al., 2021). In the context of TM, the influence of knowledge can be observed at virtually every stage of the process. It manifests in the company's ability to effectively seek and acquire knowledge from the external environment, as well as to create and disseminate it within the organization. A particularly important aspect is the firm's capacity to integrate these two sources of knowledge and utilize them effectively to develop new technologies and modify those that have already been implemented and used within the organization (Qandah et al., 2021; Quintane et al., 2011; Zheng et al., 2011; Cao & Xiang, 2012; Denford, 2013).

It is important to recognize that companies' ability to develop new specialized knowledge often transcends traditional business boundaries (Di Maria et al., 2019). This phenomenon can be attributed to the nature of clusters, which facilitate close collaboration between companies and universities, the primary providers of advanced and specialized knowledge. Such collaboration enables companies to enhance their technological resources by leveraging innovative solutions, while also mitigating the risk of failure (Scarpellini et al., 2017). Furthermore, access to external knowledge through participation in a business cluster positively influences the technological development capabilities not only of individual firms but also of the entire collaborative network (Fioravanti et al., 2023).

Collaboration on TM issues among the various participants in a business cluster can foster the initiation of intensive research and development activities, which may ultimately lead to product or process innovations (Belderbos et al., 2004). However, the collaborating partners often have differing goals, motives, and needs. For companies, the new knowledge generated through collaboration must be materialized and practically applied in their operations, which can subsequently enhance the company's economic performance and increase its competitiveness in the market. Conversely, from the perspective of universities, new knowledge should primarily contribute to scientific publications and the advancement of science, which can unfortunately hinder the achievement of the companies' objectives. These differing motivations can result in conflicts and tensions among cluster stakeholders, thereby negatively impacting the cluster's overall performance (European Commission, 2013). Therefore, addressing these diverse interests necessitates a flexible approach to managing collaboration within the cluster and a thorough understanding of the individual partners' interests (Sölvell et al., 2003; Albahari et al., 2019).

It is important to recognize that companies collaborating within a cluster function as both partners and competitors. Consequently, the opportunity to initiate joint activities may arise only when they face similar challenges within the industry or when the potential benefits of collaboration are acknowledged. Effective inter-organizational or even cross-sectoral collaboration often hinges on the ability to identify interdisciplinary solutions. Additionally, it is noteworthy that collaboration among companies fosters a sense of mutual trust, which in turn facilitates the acquisition and dissemination of external knowledge, thereby driving innovation in products and processes. Through this collaborative approach, firms can overcome information barriers and gain access to new knowledge and technologies, which can yield further potential benefits (Murillo-Luna & Hernandez-Trasobares, 2023).

Collaboration within a cluster enables companies to adopt an open innovation approach, which facilitates the overcoming of barriers and the transfer of knowledge among cluster partners. Most importantly, it contributes to the overall development of knowledge within the company, allowing cluster stakeholders easier access to various types of resources and opportunities (Xie & Wang, 2020). Close collaboration among different cluster stakeholders can serve as a catalyst for addressing industry challenges while providing firms with opportunities to reduce risks or costs and enhance their competitive advantage (Krawczyk-Dembicka & Urban, 2024).

It is widely accepted that researchers identify TM as a latent form of competitive advantage for companies (National Research Council, 1987).

However, the literature indicates a significant need for a deeper understanding of this topic (Yubo et al., 2023), as TM is inherently complex (Sahlman & Haapasalo, 2012). In particular, there is still limited knowledge regarding TM within business clusters, which are increasingly emerging as hubs for the development of new technologies.

Research methodology

The Metal Processing Cluster is bottom-up initiative that unites scientific and research institutions, business environment organizations, and enterprises engaged in the metal processing sector in Poland. Established in 2007, the cluster has been functioning continuously, primarily in the north-eastern region of the country. At the time of the survey, a total of 74 entities were participating in the cluster, of which 60 companies met the criteria of a business entity involved in production activities pertinent to metal processing and were thus eligible for inclusion in the survey process.

The research employed a survey methodology. A questionnaire featuring items scaled on a five-point Likert scale was developed and disseminated utilizing Computer-Assisted Telephone Interviewing (CATI) and Computer-Assisted Web Interviewing (CAWI) techniques. Additionally, a series of face-to-face meetings were conducted with respondents. Participants in the survey included business owners, board members, and executives from engineering or manufacturing sectors. Ultimately, 54 questionnaires were deemed valid and were submitted for statistical analysis and exploration. The reliability of the survey questionnaire was assessed, yielding a Cronbach's α coefficient of 0.906, which, according to the literature, indicates a very high level of internal consistency (DeVellis, 2003).

The research employs Structural Equation Modelling (SEM) utilizing Partial Least Squares (PLS) methodology, as outlined by (Hair et al. (2022). SEM facilitates the consideration and estimation of linear and/or causal relationships among multiple exogenous and endogenous constructs, thereby advancing theoretical understanding and explanatory frameworks (Babin & Svensson, 2012). PLS-SEM is characterized as a soft modelling approach that does not impose strict assumptions regarding data distribution (Wong, 2013).

Furthermore, it has demonstrated efficacy in scenarios involving small sample sizes and non-normally distributed data (Magno et al., 2024). The method's utility is further underscored by its causal-predictive nature, rendering it appropriate for achieving a balance between explanation, prediction, theory development, and the formulation of inherently predictive recommendations (Becker et al., 2022; Sharma et al., 2023). PLS-SEM is increasingly recognized as vital for models of success factors (Aquilani et al., 2017; Carmona-Márquez et al., 2016) and for the examination of competitive advantage (El Shenawy et al., 2007; Sciarelli et al., 2020), particularly within the context of business clusters. Additionally, some studies indicate that PLS-SEM path modeling is suitable for confirmatory factor analysis and exhibits greater reliability and accuracy compared to alternative modelling approaches (Afthanorhan & Afthanorhan, 2013).

The implementation of SEM methodology necessitated the formulation of a series of latent or unobservable constructs, each characterized by multiple measured variables (Babin & Svensson, 2012). The data were analysed in conjunction with established theoretical frameworks and the findings from qualitative research conducted among companies within the business cluster. The results obtained were processed through descriptive statistical methods, and a correlation matrix analysis was performed. This approach facilitated the identification of factors influencing various stages of TM, as well as the practices most commonly employed by the companies participating in the studied cluster. Following a comprehensive analysis of the results, it was determined that some of the identified benefits of cluster participation were also associated with specific stages of TM.

One direct variable (non-latent) and five latent variables have been considered as constituting specific research parameters to be examined by SEM procedure. The Collaboration (Coll) is a triggering variable of the model, it is composed of four elements and represents the collaboration between participants of examined business cluster. The variable Knowledge Acquisition (KnowA) expresses the way in which companies engaged in the cluster acquire knowledge related to TM. It includes three components. Active search for new technologies (ASear) describes the four methods used by the surveyed companies in the technology search phase. Technology Development (TDev) variable is characterized by two elements related to the active practices of participants in this stage of TM. Market Proactivity (MPro) includes two research elements related to the expansive behaviour of companies in new markets and niches by exploiting the potential of cluster membership. The last variable is the duration of TM activities (Time), which is a direct (non-latent) variable. This variable represents the effect of collaboration in/through the cluster on reducing the duration of TM activities. For each variable constituting the model, the abbreviated names are provided as indicated in parentheses, the average scores (on a 5-point scale) for each survey item are presented in Table 1 below.

Table 1
Characteristics of SEM variables

SEM Variables	Elements Characterizing the SEM Variables	Average score
Collaboration (Coll)	Opportunity to collaborate with new business partners	3.4
	Opportunity to collaborate with research and development institutions	2.4
	Opportunity to collaborate with business support institutions	2.4
	Ability to collaborate with regional governments and other authorities	1.9
Knowledge Acquisition (KnowA)	Exchange of technology knowledge and information between companies	3.6
	Exchange of experience and best practices among cluster members	3.5
	Access to specialized training	3.6
Active Search for New Technologies (ASear)	Participation in trade fairs and exhibitions	3.7
	Analysis of offers from other competing companies	3.1
	Market/industry analysis	3.3
	Analysis of patent databases	2.1
Technology Development (TDev)	Search for new ways to apply already implemented technologies	3.2
	Analysis of opportunities to extend the functionality of already implemented technologies	3.3
Market Proactivity (MPro)	Business expansion into new markets	3.5
	Identification of new market niches	3.3
Duration of TM activities (Time)	Reducing the time required for TM activities, e.g. by acquiring technology components from other companies	2.6

The literature indicates that the minimum sample size is contingent upon the number of variables constituting a latent variable and the number of paths within a structural model. Hair et al. (2011) assert that in PLS-SEM, the minimum sample size should be determined by the greater of the following two criteria: (1) ten times the highest number of formative indicators utilized to measure a construct, or (2) ten times the highest number of structural paths directed towards a specific latent construct within the structural model. In this study, a total of 54 respondents, specifically companies engaged in a cluster structure, were successfully interviewed, taking into account the aforementioned only one latent variable, the sample size satisfies desired minimum requirements.

PLS-SEM modelling

A structural model represents a type of "multiple and interrelated correlational and causal" relationships that exist among the elements constituting a given model. It encompasses more than just "cause-and-effect" relationships (Babin & Svensson, 2012); it creates complex constructs that, when analysed simultaneously, elucidate the phenomenon under investigation. In this study, a structural model was developed based on the results of quantitative surveys conducted among companies within a business cluster (see Fig. 1). The primary objective of any business cluster is to foster collaboration among the firms involved. In this context, collaboration (the variable Coll) initiates the entire model and significantly influences and shapes the subsequent activities. Specifically, the impact of collaboration on knowledge acquisition (variable KnowA), both among cluster participants and with other stakeholders, is evident. The knowledge acquired strongly affects the actions taken by firms at two stages of technology management, each with distinct effects. These stages are technology development (TDev) and the active search for new technologies (ASear). The active search for new technologies significantly reduces the time (variable Time) required for the technology management process within companies. Conversely, the development of technology fosters proactive behaviour among these companies in the marketplace (variable MPro), which, according to the quantitative research conducted, is particularly pronounced at one stage of technology management among the surveyed firms. Although this variable is not a typical business outcome, it holds considerable significance within the developed structural model.

Developed equation model (SEM) is statistically robust and offers valuable insights into TM within the studied business cluster. The fit and quality indicators are presented in Table 2. The average path coefficient (APC) equals 0.326 with p-value less than 0.05, in accordance with the recommendations of (Kock (2017). The explanatory power of the model is primarily represented by the Tenenhaus Goodness of Fit (GoF) index (Kock, 2017).

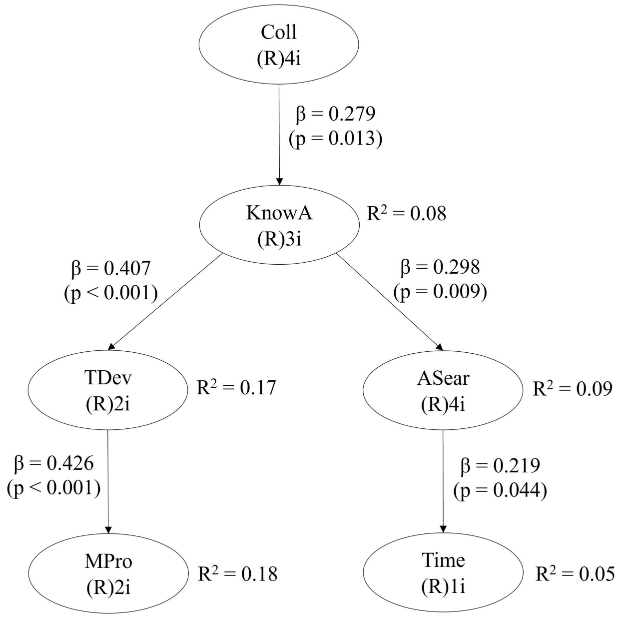

Fig. 1. The structural model of TM in a business cluster

Its level is considered medium, with a GoF value of 0.278, where values of 0.25 and above are recognized as medium. The predictive and explanatory quality of the model can be deemed acceptable. The p-values for all related variables are below the 0.05 threshold, as illustrated in Fig. 1, which also includes the path coefficient values.

Discussion

The structural model presented above illustrates how the TM sphere in companies benefits from their participation in a business cluster. It outlines the sources and key factors involved, as well as the critical effects of this engagement. The chain of dependencies depicted in the structural diagram (Fig. 1) originates from a characteristic activity of cluster structures – collaboration (Kahle et al., 2020; Connell et al., 2014). The latent variable of four elements is related to multilateral collaboration with business partners and all stakeholders from the Triple Helix, which includes research and development (R&D) institutions, business environment units, and companies. Each of these elements was evaluated by respondents on a scale of 1 to 5, as detailed in the methodology section. The rating of 2.4 for "opportunity to collaborate with research

Table 2
Model fit and quality indices

Indices type	**Indices value**
Average path coefficient	(APC) = 0.326, p = 0.002
Average R-squared	(ARS) = 0.112, p = 0.098
Knowledge Acquisition (KnowA) Average adjusted R-squared	(AARS) = 0.095, p = 0.118
Active Search of New Technologies (ASear) Average full collinearity VIF; acceptable if ≤ 5, ideally ≤ 3.3	(AFVIF) = 1.411
Tenenhaus GoF; small ≥ 0.1, medium ≥ 0.25, large ≥ 0.36	(GoF) = 0.278
Sympson's paradox ratio; acceptable if ≥ 0.7, ideal = 1	(SPR) = 1.000
R-squared contribution ratio; acceptable if ≥ 0.9, ideal = 1	(RSCR) = 1.000
Statistical suppression ratio; acceptable if ≥ 0.7	(SSR) = 1.000
Nonlinear bivariate causality direction ratio; acceptable if ≥ 0.7	(NLBCDR) = 0.800

and development institutions" and 1.9 for "ability to collaborate with regional governments and other authorities" (Table 1) corresponds to the low level of variance indicated by SEM, which is attributed to the limited number of companies examined. Notably, among the stakeholders involved in collaboration, there is an element concerning authorities (both regional and beyond). This is undoubtedly linked to the fact that the business sector under study is included in the list of regional and national smart specializations, thereby qualifying it as a beneficiary of various forms of public interventions. At the same time, the results may indicate the untapped potential of clusters in terms of collaboration. The small number of R&D units and local government units involved in the business cluster means that their collaboration with enterprises is limited to the implementation of projects requiring the involvement of various types of stakeholders and to the implementation of the statutory objectives of the cluster. R&D units are mostly engaged in the so-called "close collaboration group", where they closely collaborate with selected enterprises, but this does not apply to all units. This is possibly the reason that the goodness of fit of the model is not high (GoF = 0.278, Table 2). In order to enhance collaboration among individual cluster stakeholders, it is advisable to establish clear strategic goals for the cluster's activities and to streamline the procedures governing collaboration, which often vary for each party.

The involvement of companies in the activities of a business cluster enables these entities to acquire and accumulate valuable knowledge (KnowA variable), which is particularly evident in the SEM model at two stages of technology management. Both the stage focused on the search for new technologies (ASear) and the stage dedicated to the development of existing technologies (TDev) were strongly emphasized during the empirical research and were predominant among all seven stages of technology management analysed in the study (identification/search, selection, acquisition, development, exploitation, protection, and withdrawal of technology).

According to the respondents, the acquired knowledge should originate from external sources, including other companies and specialized training programs. Knowledge generated from the experiences, both positive and negative, of other entities within the business cluster is invaluable, as these entities operate under similar conditions and in comparable markets, allowing them to learn from one another. The exchange of knowledge and experience during the technology search stage can provide insights into the technological possibilities, potential, efficiency, and limitations of a given technology, as well as practical advice related to its exploitation. Conversely, at the technology development stage, it can serve as a valuable resource for configuring individual parameters of technology and equipment, as well as offering guidance on the development of new products or the enhancement and modernization of existing products and technologies.

The type and scope of knowledge acquired from business clusters depend on the specific stages of technology management mentioned above. The stage of technology exploration necessitates domain knowledge, which enables an assessment of industry specifics and the value of available technological solutions, ultimately leading to the selection of the most advantageous options. The practical experiences of other companies and technology users are invaluable in this context. Conversely, the technology development stage requires access to architectural knowledge, which focuses on understanding the structure of a given technology. This type of knowledge fosters new ideas, provides practical examples, and explores new technological possibilities, thereby expanding the functionality of implemented technologies. It encompasses knowledge of new applications for existing technologies and their potential for improvement, as well as knowledge that facilitates the creation of innovations. It is important to note that the aforementioned activities aimed at technology development are closely linked to the proactive approach of companies in exploring new markets and identifying market niches (MPro). This proactive stance is highly beneficial for long-term business development and competitiveness. The left path of the observed model highlights the strategic dimension of TM in relation to the company's involvement in the business cluster. The connections between knowledge acquisition (KnowA), technology development (TDev), and market proactivity (MPro) demonstrate the strongest relationships among the variables. According to the data presented in Fig. 1, the path coefficients are 0.407 and 0.426, respectively, representing the highest values in the entire model.

These relationships are also evident in the literature, which indicates a correlation between companies with advanced technology management capabilities and improved business outcomes (Wu et al., 2010).

Furthermore, R&D management is regarded as a continually evolving strategic tool essential for the long-term competitiveness of a company (Edler et al., 2002). The developed structural model, along with the aforementioned observations from the literature, confirms the validity of the inherent perspective of TM from a strategic standpoint, aligning with findings from several studies (Cetindamar et al., 2009; McCarthy, 2003). SEM demonstrates that participation in a business cluster is a significant factor in the strategic role of TM within a company. Additionally, architectural knowledge appears to be particularly crucial in the strategic dimension of TM. It allows access to very valuable and rare tacit knowledge, which is incorporated into the organizational practices of the company. Effective transfer of architectural knowledge between cluster partners has an impact on the results achieved by the cluster (Leszczyńska & Pruchnicki, 2016).

Looking at the right path of SEM (Fig. 1) one can identify specific benefits arising from the initial stage of TM – the technology search. This stage significantly reduces the time required for activities undertaken in both this and subsequent phases of TM. The reduction in time stems from the knowledge gained through participation in business clusters, and its impact is evident across all aspects of TM. A company that leverages best practices and the experiences of other organizations can save considerable time and effort in all activities, from technology search to selection, acquisition, and development. The time invested by a company in bringing new technology to market is crucial in today's era of global competition, which necessitates increased flexibility and efficiency during the technology or product development phase (Lu et al., 2000; Rafinejad, 2007; Haddad, 1994; Vesey, 1992).

Additionally, shortening the time of TM activities is possible thanks to "acquiring technology components from other companies", which the respondents rated at a level of 2.6 (Table 1). Although this rating may not appear particularly high compared to other factors, it is comparable to some values of the Collaboration (Coll) variable factors that are significant for this study and should be considered alongside the low level of variance. This observation leads to an important conclusion: the model reflects the behaviour of a limited number of companies within the studied business cluster, which, as a result, derive greater benefits from their collaboration. The conclusions drawn goes in line with facts known about the cluster, there exists "the close collaboration group" within it, its participants (selected companies) probably derive real, measurable benefits from their involvement in the cluster. Conversely, companies that do not belong to this group often express scepticism during public discussions regarding the potential benefits of the cluster.

To summarize, it can be stated that, according to the structural modelling (SEM), two TM stages are particularly beneficial regarding the impact of clusters on whole TM: technology search and technology development. These stages are highly dependent on knowledge acquired from external sources.

Conclusions

This study was conducted in the metal processing industry, where breakthrough technologies that have the potential to revolutionize the sector emerge infrequently. Nevertheless, it serves as an example of a highly interesting and stable industry. The objective of the study was to investigate the internal collaboration among members of a business cluster concerning technology management. The findings indicate that the multidimensional collection facilitated by the business cluster enables the acquisition of technological knowledge from external sources, thereby reducing the duration of TM activities and significantly enhancing market engagement. The knowledge derived from the cluster is particularly utilized by companies during two key stages of TM: the search for new technologies and technology development. Membership in a cluster proves advantageous for companies during those phases of TM where knowledge plays a critical role. The equation modelling method (SEM) revealed that architectural knowledge is of paramount importance in the TM domain for companies involved in the business cluster structure. This type of knowledge pertains to the configuration and reconfiguration of technologies, as well as the redevelopment of existing and new products. During the technology development stage, this knowledge is especially crucial. Companies that leverage this cluster knowledge tend to be more proactive in the market, actively seeking new opportunities and identifying market niches. This trajectory of the developed model can be viewed as strategic; companies capitalize on strategic advantages rooted in their cluster involvement. The observed chain of influence is significant for long-term business development and warrants further investigation. Researchers should also focus on the in-depth identification of architectural knowledge and its impact on the creation of new technologies and products, which may lead to the development of breakthrough technologies in the industry in the future.

Although the assumptions of the model presented in this study pertain to the stable machinery industry, the authors assert that they can also be applied to other, more dynamically developing sectors, such as information technology or biotechnology. However, this application necessitates further research which will consider the unique characteristics of these industries, particularly concerning the duration of the technology life cycle. Other assumptions, such as the intensity of collaboration, mechanisms for knowledge collection and exchange, and methods for acquiring new technologies, appear to be quite similar; however, they require thorough examination.

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