The Exploratory Impact of Technology, Organizational Concepts, and Employee Training on Business Performance

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***Abstract*—This paper analyzes exploratory, the findings from Finland's 2022 European Manufacturing Survey (EMS22). The primary focus is on the narrowed Development of Competitiveness and Employment Situations (DCES) measures, measured by parameters such as Annual Turnover (AT), Number of Employees (NE), Manufacturing Capacity Utilization (MCU), and Return on Sales (ROS). The interaction between Organizational Concepts (OCs) and Key Enabling Technologies (KETs) is explored in the context of manufacturing, with attention to Organizing Production (OP), Production Management and Control (PMC), Training and Competency Development (TCD), Production Control (PC), Automation and Robotics (AR), Efficiency Technologies (ET), and Simulation Data Analysis and Additive Manufacturing (SDA). The investigation seeks to understand how OCs and KETs interplay with the key components of DCES in the EMS22 environment. Results illustrate the influence of these aspects on AT and NE, with significant implications for MCU and ROS. Interestingly, the impact of PMC on ROS was marginal, suggesting a contentious relationship. TCD appears to play a supporting role in this context.**

***Keywords*—Industry 4.0, organizational concepts, manufacturing key enabling technologies, correlation modeling**

I. Introduction

This study investigates techno-organizational practices within the Finnish manufacturing industry. The approach is Technology, Organization processes, and People (TOP) to address the technology and organizations from the past science output perspective.

People to Artifact, User, Task, Organization, Situation (AUTOS) framework forming an experimental research design (Boy, 2020). The study explores the literature behind the historical development of the sector to understand the impact of the technologies used on the firm's performance and transition (John *et al.*, 2022). This study's findings are based on surveys conducted among firms' people, where data was collected primarily from C-suite executives and other managerial roles. This EMS22 data was obtained for a cross-sectional analysis of the firms' DCES (Armbruster *et al.*, 2005). In the past, the focus has often been on isolated factors affecting manufacturing key enablers and organizational performance. Used performance (growth, labor market, stimulated utilization) is a standard economic and organizational measure in EMS22. This study aims to provide a perspective, analyzing the full spectrum of OCs before narrowing it down to specific practices and production management gaps (Coriat, 2002) of KETs. This study research methodology follows multi-method, quantitative research to ensure a comprehensive assessment. The analysis involved short, concise explanations and broad data acquisition methods, striving to reach most corporate executives through various channels.

EMS22 survey has a historical significance, having previously analyzed data relating to technological and non-technological organizational innovation. Technological key enablers have been defined differently in the context of European Horizon (European Parliament, 2023). Within EMS22, the study promotes the key manufacturing enablers, which are combinations of key enablers. This investigation has provided insights into which EU countries are poised for change through organizational innovativeness and the utilization of KETs (Armbruster *et al.*, 2005). In this study, the self-reported performance of Finnish manufacturing firms is evaluated for the case of the fiscal year 2021 and comparing these results with other cross-sectional variables. This analysis further examines how OCs and KETs impacts companies' capital utilization. Previous studies have demonstrated the multivariates between used practices and correspondence (European Commission *et al.*, 2015). Methods used in this study incorporate analysis of correlations of dummy variables associated with the AUTOS in the companies for revenue. The technical data analysis conducted in this study explores the interconnections between EMS22 factors after the literature review to conclude and govern future research.

II. Literature Review

In the industrial landscape, two critical factors contribute significantly to a company's competitive position: OCs and KETs, interconnecting into a competitive advantage of a techno-organization (Barney, 1991; Teece, 1997). OCs primarily include organizational structures and systems that enable effective operation and decision-making across sectors (Mintzberg, 1989). In contrast, KETs of manufacturing refer indirectly to the combination of infrastructures for innovation and competitiveness (European Parliament, 2023). In fully developed organizations, techno-organization performs at various levels at all hierarchies (Mintzberg, 1989). The study research context suggests the development is fully developable. Past research has attempted to analyze the relationship between OCs and KETs and the overall impact on the manufacturing company's performance. Understanding the depthness of the overall impact in research purpose was sought utilizing keywords relevant to the study context as found in Fig. 1.

Close behind the last ten years of progress, the analysis of Scopus documents related to manufacturing shows high-interest areas, with search syntaxes: "production AND control AND manufacturing" (47,128 documents) and

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"organization AND manufacturing" (32,768 documents) seeing the most extensive research. Other notable areas of focus include "efficiency AND technologies AND manufacturing" (19,135 documents) and "production AND management AND control AND manufacturing" (11,645 documents). The role of emerging technologies and automation in categories like "enabling AND technologies AND manufacturing" (5,465 documents) and "automation AND robotics AND manufacturing" (3,817 documents). Despite having fewer documents, the importance of skill development and data-driven manufacturing approaches is underscored in "training AND competency AND development AND manufacturing" (165 documents) and "simulation AND data AND analysis AND additive AND manufacturing" (515 documents), respectively (Source: Scopus 26.6.2023).

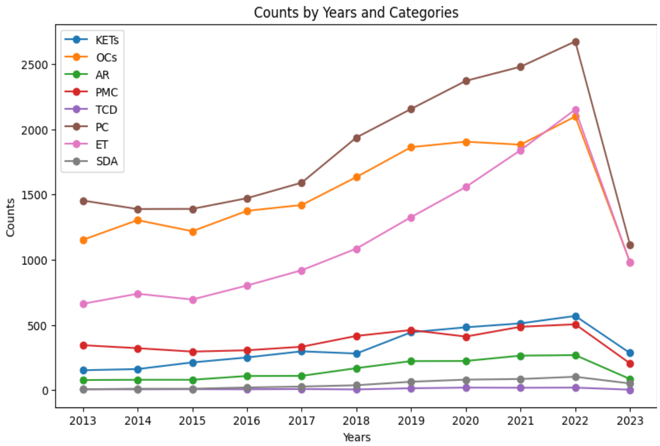

Fig. 1. Scopus documents related to manufacturing in the last 10 years.

As depicted in Fig. 1, certain themes like "Production Control" "Efficiency Technologies" have been extensively explored, downright, intersecting with this new organizational practice, while others have received comparatively less attention, signaling potential opportunities for future research of new tech and sustainability, because they must surely exist. Interestingly, there is a correlation between the complexity of a theme and the quantity of related articles. More topical, "Training and Competency Development" and "Simulation and Additive Manufacturing" have low saturation, underrepresented. However, these studies need to address manufacturing in Finland, which interrelates directly within a comprehensive measurement framework in Finland. This leaves a gap in understanding the synergistic effects of OCs and KETs on the firm's performance as a human factor with capital performance, e.g., labor turnover rate (Ni, 2022) outcomes interacting within the infrastructure based in information (Abualoush *et al.*, 2018).

This study aims to bridge this gap by comprehensively exploring the interaction between OCs and KETs and how this relationship influences crucial performance indicators such as AT, NE (Ni, 2022; Lee, 2017; Guzeller *et al.*, 2020), MCU (Okeoma, 2022), and ROS profit (Wang & Li, 2021). The reformation process is the transformation towards a more adaptable, innovation-centric paradigm for firms coined I4.0. EU papers with varying objectives emphasize the modernization of key regional challenges through funding and fostering employment growth. The focus will be on the following technological trends in the field of I4.0 via KETs (SDA, AR, PC, and ET) (European Commission, 2022). In developing countries, ET has proven to improve MCU at the state level (Cheng, 2022), while inflation-bound capital formation ought to result in the lag of capital acquisition autoregressive distributively (Bank-Ola *et al.*, 2020). Environmental regulations, shown in terms of ET adoption, have negatively impacted manufacturing (Wang & Li, 2021).

A. Organization Concepts

Digitalization has changed manufacturing and its processes' sustainability progressively (Noiki *et al.*, 2022). The various areas of the EMS22 organizational perspective are how the organization maintains the manufacturing operations.

1) Organizing production in organizational context

OP encompasses manufacturing processes' strategic arrangement and coordination to ensure optimal efficiency (Rahman *et al.*, 2021). There is a role of organization platformization in integration into a circular economy (Cantù *et al.*, 2021). This strategy involves carefully orchestrating production processes to ensure maximum utilization of resources and minimize waste (Prause, 2018). The effective implementation of OP strategies directly affects MCU and ROS, key indicators of a firm's competitiveness (Serrano-García *et al.*, 2022).

Modern advances such as AR and ET have been instrumental in manufacturing for energy efficiency (Ding *et al.*, 2023). Integration especially supports optimizing OP on the I4.0 maintenance level (Di Nardo *et al.*, 2021). Over the coming decade, future trends above 5.0 will allow for real-time adjustments and precision control over production processes (Ortiz *et al.*, 2020).

2) Production management and control in organizational context

PMC deals with the process's maximization of efficiency and product quality (Coriat, 2002). It includes activities such as scheduling, controlling, and monitoring production, as well as inventory and production cost management included in the manufacturing execution system (MES) (Kletti, 2007; Saenz de Ugarte *et al.*, 2009; Sauer, 2009).

Incorporating KETs, such as data analytics and Machine Learning (ML), has revolutionized PMC, providing real-time data analysis and predictive capabilities (Bäckström & Bengtsson, 2018). Industry 4.0 (I4.0) technologies like cyber-physical systems and cloud computing have further streamlined PMC, leading to decoupled organizations on autonomous control of production processes (Khalil *et al.*, 2016).

The most prominent role of manufacturing is increasingly played by technology, and in the context of the organization, it is important to emphasize people to achieve TOP. Environment system integration for people's security is important, and in digitalization, it is a tricky area for the future of manufacturing, seen as increasing sustainability (Mustapic *et al.*, 2023). Digitalization-based environment awareness is an Industry 5.0 key enabler (Trstenjak *et al.*, 2023).

3) Training and competency development

TCD is critical for developing necessary skills and competencies among the workforce in manufacturing firms regarding safety leadership (Edmondson, 2003). The growing complexity of manufacturing processes, particularly with the adoption of advanced technologies like AR and ET. This necessitates continuous upskilling and training of the workforce. Developable from industry operations to curricula context (Gunasekaran & Ngai, 2012). Labor numbers in firms have been turned down because of the talent acquisition, development, and retainment plans for sustainable instead of the number of resources sawn in labor reductions (Khatri *et al.*, 2010). Employee talent management is part of a broad concept that recognizes talent, globalized mobilization services, and competitive remuneration (Yon, 2020).

Furthermore, TCD emphasizes soft skills such as problem-solving, critical thinking, and teamwork, which are essential for fostering an innovative and efficient working environment. Employers must respond to employees' requirements by selecting forces to provide the training needed (Yon, 2020). Sustainability-based problem-solving is, metaphorically, an efficient power transfer, as utilization becomes new technologies and emphasizes soft skills (Song *et al.*, 2023).

B. Key Enabling Technologies for Manufacturing

1) Production control is the key enabler of manufacturing

Key Enabling Technologies (KETs) are in the study context more into manufacturing key enablers from the EMS22; manufacturing key enablers in a broader context than the Panel for the Future of Science and Technology (2021) suggested European Parliamentary Research Service on KETs.

PC significantly impacts the smooth functioning and efficiency of manufacturing operations. Effective PC manages scheduling and task execution. Double-directional indirect streamlining of the production line from raw material supply to finished goods delivery via the use of IoT and industry technology could contribute to the implementation of smart factories (Kim *et al.*, 2023). PC acts as the intersection of Entrepreneur Resource Planning (ERP) and Machine/Product Data Acquisition (MDA/PDA), helping maintain product lifecycle management (Liu *et al.*, 2020). The advent of the Internet of Things (IoT) and Machine Learning (ML) has further empowered PC, transforming physical signals into digital data that provides valuable insights for continuous improvement and fosters R&D activities (Kaiser *et al.*, 2019; Oluyisola *et al.*, 2022). Digital transformation has facilitated the integration of technologies such as Radio-frequency Identification (RFID) and Quick Response (QR) codes, enhancing supply chain management, product traceability, and real-time tracking (Gunasekaran & Ngai, 2012).

2) Automation and robotics technologies in manufacturing

AR is the foundation of I4.0, transforming manufacturing processes, enhancing efficiency, and consequently boosting productivity and employment. AR's integration in manufacturing allows functions to proceed independently of human presence, ensuring high quality (Kinkel *et al.*, 2015). A recent EU study revealed a strong correlation between AR and productivity gains in SMEs (EC, 2019). Higher MCU has been achieved through AR, reducing time spent on servicing and installation and thus minimizing production loss (Kinkel *et al.*, 2015; Kleine *et al.*, 2011).

3) Efficiency technologies for manufacturing

ET is instrumental in achieving sustainable manufacturing processes. ET tackles environmental and social concerns such as waste management, energy efficiency, and resource conservation through the implementation of sustainable technologies and practices. Aiming for a meta-level of efficiency, ET's approach is characterized by three layers. The first is compliance with EU directives aimed at reducing greenhouse gas emissions, promoting renewable energy, and reducing waste generation (Lyons *et al.*, 2021). The second layer involves leveraging Life Cycle Assessments (LCAs) data for financial management to reduce operating costs, increase competitiveness, and meet regulatory requirements (Abidi *et al.*, 2022; Lindow, 2013). The final layer targets the assessment and minimization of manufacturing waste, promoting the efficient and sustainable use of resources (Venkataramana *et al.*, 2013).

4) Simulation data analysis and additive manufacturing

SDA plays a pivotal role in the application of KETs. Laser-based additive manufacturing, compared to laser-based non-traditional manufacturing, is subject to fewer input resources, also bearing case specifically comparison against subtractive manufacturing for good, lubricated rotation. Manufacturing benefits have a dependence on competitiveness: performance of sales within the market in various sectors. (Johansen & Akaya, 2022.).

The future forms expectations based on managing information beyond the projected 175 zettabytes by 2025. SDA-based tangible system development operates on data- or simulation on sustainable model-based manner first approaching lifecycle assessment via simulated robotics machinery (European Commission, 2022b; 2016.). In the journey from design to decommissioning of a product, SDA provides a comprehensive data-based product simulation and retirement by analysis, which is crucial for efficiency planning (Pufahl & Weske, 2017; EC, 2018). SDA's application includes harnessing user data for simulation, enhancing product quality, and improving manufacturing processes. In I4.0, SDA creates digital mirrors of factories, products, and workers for better management and control, helping businesses remain competitive through innovation (Straßburger, 2019; Corallo *et al.*, 2022).

5) Refining manufacturing

Refining the integration for effective implementation of OCs (OP, PMC, and TCD) are vital for enhancing the competitiveness of manufacturing firms. These KETs (PC, AR, ET, and SDA) are integral to modern industry's adaptation to the I4.0 revolution. They drive competitiveness and innovation, enhancing efficiency while promoting sustainability.

III. RESEARCH PROBLEMATIZATION AND HYPOTHESES

Environment modeling over statistics with mathematics gains support from the literature mentioned above review. Growth in terms of turnover is a contradictory measure. This focus gains convergent validity in cross-sectional studies, enlightening on how statistical sciences is usable, particularly in terms of method, to process the EMS 2022 dataset dimensions. Crucially, Statistical Package for the Social Sciences (SPSS) in-built statistical analyses offers an independent perspective on observations, regardless of the low spectral dimension saturation (n = 123). The Research Questions (RQs) identified serve as the heart of the research, asking for an exploration into the intersection of terms with a primary focus on the DCES.

OCs are investigated across three primary areas: the OP, PMC, and TCD practices. The RQs prompt an analysis of how these concepts influence AT, NEs, MCU, and ROS. Each RQ is further broken down into sub-RQs to encapsulate the objective.

Machine learning-governed Supervised learning-based statistical sciences processing software enable interpret the data further. The research also problematizes the role of single- to multiclass clustering of organizational innovation practices, giving an alternative approach to observing the variable-related phenomenon. The interdisciplinary actions aim to achieve sustainability-activated growth, further underscoring the importance of the convergent validity of the cross-sectional approach.

In addition to the RQs, the following sub-RQs were formulated to address the usage of KETs. How are the DCES of companies considered influenced by the utilized KETs and OCs?

This question aims to understand the techno-organizations practice used to enhance competitiveness. By mapping these hypotheses according to the objectives of the study and database findings, the research can simulate sub-RQs recursively as part of the top-down themes related to latent entities. The outcome is the establishment of hypotheses for OCs in Table 1, and for KETs hypotheses found in (Heilala *et al.,* 2022).

Table 1. OCs construct correlations hypotheses

	AT	NE	MCU	ROS	OP	PMC	TCD
AT	I						
NE	n.s/n.c.	I					
MCU	n.s/n.c.	n.s./n.c.	I				
ROS16	n.s/n.c.	n.s./n.c.	n.s./n.c.	I			
OP	n.s./n.c.	n.s./n.c.	n.s./n.c.	n.s/n.c.	I		
PMC	n.s/n.c.	n.s/n.c.	n.s/n.c.	n.s/n.c.	n.s/n.c.	l	
TCD	n.s/n.c.	n.s./n.c.	n.s/n.c.	n.s/n.c.	n.s/n.c.	n.s./n.c.	l

Hypothesized variables axioms not having significant correlation/ correlation (n.s./n.c.)

IV. Methodology

A. Research Setup

The study offered a compilation of the initial results of the EMS22 in Finland. The information was obtained from various sources such as the internet web portal (EMS, 2022), newspaper columns (Six, 2022; Eurometal, 2022; SATL, 2022), and an e-mail newsletter (Webropol, 2022). A separate printable survey form was circulated among company managers or legally competent individuals with the capacity to give insightful responses. These individuals, often responsible for compiling company responses, helped achieve a broad information collection.

B. Instruments Used

This study research tool was developed from the responses of the EMS22 Finland. Based on manufacturers' perspectives, the data entries were taken from the DCES and the KETs. The selected range was covered from (m23a1), including Annual Turnover (AT, m23a1), Number of Employees (NEs, m23b1), Manufacturing Capacity Utilization (MCU, m23h), and Return-On-Sales (ROS, m23i1–m23i5). Furthermore, the range covered Production Control (PC, m09a1–m09g1), Automation and Robotics (ARs, m09h1- m09i1 and m09q1–m09r1), Efficiency Technologies (ETs, m09k1–m09l1), and Simulation, Data-analysis, and Additive (SDA, m09m1–m09p1) manufacturing technologies. (EMS 2022.).

C. Analysis Protocol

The adopted multi-method approach primarily centers on quantitative modeling to provide insights of Sørensen's dice into the relationship and intrinsic states of variables. An example of this is the interpretation of the Jaccard index (Costa, 2021). This is the linkage between a company's growth as F1-score, represented experimentally by turnover, and the employed and deployed factors. Signifying the true and false positives of the sample with less emphasis on the outliers. The study seeks to ascertain the dataset's intrinsic interplay. For example, taking a high variable A ("AT") normalized also implies a low variable normalized B ("AR") and interprets high C ("NEs") within the sample. This focuses on the causal reliability among the variables, analyzed using multivariate methods and rotation.

D. Descriptives

The descriptive data from EMS22 analysis results (Table 2) and correlation found in another book (Heilala *et al.,* 2022) provide measures of various variables used in these studies. The response range from minimum to maximum indicates the array of values for variables like AT, NE, and MCU, among others. AT provides an overview of the annual revenue of the companies surveyed, reported in millions of Euros. The NE represents the total human resources of the surveyed companies. MCU from both Tables (Heilala *et al.,* 2022) measures the extent to which companies' primary operations are used. Meanwhile, the ROS in both studies gives a scaled performance index before tax, with values ranging from 1 to 5 and denoting different profitability margins (negative, 0%–2%, >2%–5%, >5%–10%, and >10%).

An important element in both Tables (Heilala *et al.,* 2022) is the binary classification indicating whether the companies employ specific OCs methods or KETs. These include KETs for manufacturing (PC, AR, ET, SDA) technologies.

The relations among these variables are analyzed using embedded correlation modeling. This approach involves computing the sum of variables for each dimension of the EMS22 and dividing it by the total number of variables. This method allows for a comprehensive understanding of the interaction and relationship between the different variables considered in the study.

Table 2. OCs construct descriptives

	MIN	MAX	M	MED	MOD	STD	SKEW	KURT	SUM	VALID
AT	0.000	339	26.219	6	1	52.445	3,767	17.641	2071	79
NE	3	600	84	40	12	115.41	2.335	5.98	7140	85
MCU	0.000	100	66.672	75	80	28.975	-1.227	0.664	4267	64
ROS	1.000	5	3.423	4	5	1.567	-0.509	-1,29	267	78
OP	0.000	1	0.493	0.600	0.600	0.336	-0.025	-1.189	60.60	123
PMC	0.000	1	0.549	0.667	0.667	0.278	-0.207	-0.823	67.50	123
TCD	0.000	1	0.525	0.600	1.000	0.344	-0.115	-1.209	63.00	120

Table 3. OCs construct correlations

	AT	NE	MCU	ROSI6	OP	PMC	TCD
AT	1						
NE	0.905 ****	1					
MCU	0.243 **	0.18 *	1				
ROS16	0.237 **	0.176 *	0.299 ***	1			
OP	0.254 **	0.255 **	0.062	0.16	1		
PMC	0.403 ***	0.446 ****	0.161	0.323 ***	0.422 ****	1	
TCD	0.289 **	0.281 **	0.181 *	0.164	0.314	0.28 **	1

****p<.001, ***p<.01, **p<.05, *p<.01

The descriptive data analysis reveals key insights about the DCES and KETs parameters of interest. Certain trends are noticeable for the DCES sample, which includes AT, NE, MCU, and ROS. The AT ranges from zero to 339 million euros, with a grand mean of 26.219 million euros and a standard deviation of 52.445 million euros. The distribution shows a positive skewness, indicating a larger player in the sample and some smaller enterprises. Interestingly, NE shares similar distributional characteristics with AT.

For MCU and ROS, the distributions are negatively skewed in a platykurtic manner, showing less peakiness. Despite these variations, an intriguing observation is that the grand mean of 3.42 for ROS implies positive returns for corporations on average. However, AT's positive skewness and leptokurtic peakedness indicate that some larger players are more prominent in the sample, necessitating further correlation analysis for more comprehensive insights (EMS 2022 analysis results).

E. Correlation Modeling

The variables from the DCES and KETs instruments were standardized (Z-score). Analyses were then launched within the SPSS analysis program, tested for reliability, and found processable. Parent variables were computed from child variables using arithmetic means in a convex combination. This step was performed to enable interpretable analysis and draw conclusions per the guidelines set in the Analysis protocol.

In this section, multivariate methods are used to analyze the explanatory variables. The non-multicollinearity of sum variables (Paollella, 2019) ensures that a strong correlation does not exist. The utilization of variables hinges on obtaining a linear outcome (Metsämuuronen, 2001). Hence, the statistical approach relies on all variables being continuous and originating from a random sample.

It is important to note that correlations do not necessarily test for a causal relationship between two variables; therefore, each pair must be evaluated independently (Tanni *et al.*, 2020). The reliability of multivariate analyses typically depends on having at least 40 observations per variable (Metsämuuronen, 2001; Paollella, 2019). Considering the sample size of this study (n = 123), only a sample-specific analysis can be performed.

The correlation coefficients in Table 3 and (correlation found in Heilala *et al.*, 2022) serve as predictors in the analysis. After examining the EMS characteristics, provided recommendations to support managing manufacturers' balance within Finland. The variables' multivariate test elucidates in the background analyzes minimum and maximum, while printed Table(s) shows non-standardized R and p.

Comparing OCs children (OP, PMC, TCD) to KETs parameters show underutilization as confirmed by standardized deviation, mode, and median. It is found that the KETs involved (AR, ET, and SDA) are the most significant variables for further investigation because of distributional absence characteristics (EMS 2022 analysis results).

The correlation between DCES and KETs was performed using Pearson's correlation (R), a standard measure of the linear relationship between two variables. This correlation analysis is essential to understand the variables' dynamics and derive extensive insights from the dataset's narrowed big data, hence the study's exploratory nature supported.

The correlation analysis shows that a healthy operating company, indicated by high AT, has a good NE and can generate ROS, which relies on MCU to respond to real capital utilization. Also, AR and ET's usage positively correlates with AT and NE. Interestingly, the use of PMC is common across all company cases, hinting at a potential direct relationship between them (EMS 2022 analysis results).

The analysis also revealed a strong association between AR, ET, and SDA, suggesting that companies using these technologies likely simulate and prototype their manufacturing at different levels. This connection might reduce companies' resource loss for innovating, positively impacting operational efficiency (EMS 2022 analysis results).

V. CONCLUSIONS

The findings illuminate the association between a company's DCES and the adoption of certain KETs and management strategies. The first part of the study analyzes the effect of OP, PMC, and TCD on competitiveness and employment. Findings indicate that the organization of production can positively influence AT, NEs, and MCU for top-tier firms. However, the impact on ROS is less clear. PMC shows a significant correlation with OCs for larger companies, but not all firms fully leverage this. TCD significantly influences business growth, though with variable returns, suggesting the need for tailored training approaches.

The second part examines the relationship between KET usage and DCES status. It was found that the application of PC significantly positively correlated with AT and NEs for larger companies. However, the link with MCU is less definitive and varies among firms. The use of ETs and SDA showed a weak but significant correlation with DCES, indicating that they are primarily utilized by larger companies. These findings underline the importance of OCs and KETs in improving a company's DCES, pointing to varying peaks and the interpretability of latent variables as areas for future research.

A. Limitations

The analyses in both studies showed satisfactory results, even with the inclusion of a few medium companies among the small ones. Despite the limitation of a weak decimal correlation and marginals as a threshold for interpretable results, the studies provided valuable insights into the factors that influence an organization's DCES.

CONFLICT OF INTEREST

The authors have no conflicts of interest to disclose.

AUTHOR CONTRIBUTIONS

Janne Heilala and Jussi Kantola implemented EMS22 research; Antti Salminen, and Wallace Moreira Bessa wrote this chapter's analysis view; all authors had approved the final version.

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