An Exploratory Analysis of Supply Chain Contract on Efficiency, Simulation, and Data analytics Augmentation Technologies

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Abstract—The European Manufacturing Survey 2022 (EMS22) evaluated the Finnish manufacturing industries and between advanced manufacturing technologies sustainability management systems in Finnish industrial companies. The profitability was compared under the **Development of Competitiveness and Employment Situations** (DCES) narrowed industry requirements. The study utilized EMS22 techno-organizational innovation indicators to measure performance components within manufacturing organizations. In the first part, the horizontal factors were considered thoroughgoingly with a literature review: significant growth in the Finnish industry between 2014-2018, the impacts of the COVID-19 pandemic, and the importance of integrating sustainable practices in manufacturing operations. In the second part, the EMS22 larger pool of respondees provided parities in statistical assumptions on a national scale. The implications of Supply Chain Contracts (SCC) on manufacturers and contract manufacturers were assessed in diverse Human Resources (HR) contexts by comparing the firms' employee percentages. The findings highlight the critical role of adopting Efficiency Technologies (ET) and simulation, data analysis, and additive manufacturing technologies to enhance firms' competitiveness in augmenting virtual and reality. Conversely, to expectations, companies were lagging in advanced technology adoption, particularly needing a focus on university resources-driven innovations. Firms lacking certified environmental management systems demonstrated reduced competitiveness. The survey underlines the importance of energy management systems for firms' satisfactory performance. The future of research is headed for the determinants of competitiveness on a national scale by integrating business and artificial intelligence into sustainability strategies among exploring sustainable manufacturing.

Keywords—Industry 4.0, competitiveness, employment, supply chain contracts, human resources, simulation, dataanalysis, additive manufacturing, energy management systems, environmental management systems

I. INTRODUCTION

The landscape of Finnish industrial companies has evolved significantly in recent years. The European Manufacturing Survey 2022 (EMS22) offers a critical look into the operations and strategies of these industries, targeting improving firms' key decisions and assessing their practices within a rapidly changing environment to understand the Development of Competitiveness and Employment Situations (DCES).



Fig. 1. Mostly positive trends in the long term in document counts by topic and year for contract manufacturers and manufacturers, plotted on a logarithmic scale. Each line represents the documents with solid lines for "contract manufacturing" and dashed lines for "manufacturer." The topics include "simulation," "data analysis," "additive manufacturing," "energy," "environment," "performance," "competitiveness," "turnover," and "employment." The number of documents per year was displayed on a logarithmic scale of several orders for magnitude shown in the function of the decade. (Source: Scopus 26.6.2023.).

This research is comprised of two parts. The first part was conducted through a Scopus search. The data plotted in Fig. 1 represent the number of documents returned from a database search. Second, a multimethod-embedded correlation model was applied from the EMS22 data. A literature review related to industry measurement period and requirements regionally with relevant sources for adjusting to establish new science in technology. The study focused on key firm metrics, specific inquiry lines, or executed search queries for Fig. 1. Topics of each topic range of interest are followed, substituting the {topic} with each additional with a more detailed search term. The

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Fig. 1 y-axis (number of documents) is plotted on a logarithmic scale to visualize differences and trends better. This scale transformation shows several orders of magnitude for establishing theoretical domain knowledge. (Source: Scopus 26.6.2023).

The Finnish industry witnessed a growth of over 20% between 2014 and 2018, with a notable increase in employment rates (European Commission, 2019). The industry has been resistant to global challenges. The COVID-19 pandemic brought significant disruptions, including temporary layoffs (Hanhinen, 2022; YLE, 2022). Such layoffs often result from operational challenges, financial strains, or the need to adapt to new technological advancements (Eurofound, 2022). The pandemic's effects severely impacted manufacturing, though support for firms and workers mitigated some shocks (EK 2020; OECD, 2023).

In consideration of such challenges, sustainable manufacturing has come to the forefront. The importance of integrated platforms, computer-aided technologies, and practices focusing on energy density and power-saving cannot be understated (CADMATIC, 2023; Battisti et al., 2022). As Finland navigates its role as a high-tech exporter, it addresses high labor costs for operations maintained with significant R&D investments. It accommodates regulations and cultural factors for world-class quality (Celik & Alola, 2023). This landscape requires Finnish industries to consider more than just traditional metrics. Firms also prioritize sustainable HR development, focusing on training the workforce for Industry 4.0 and the upcoming Industry 5.0 and Industry 6.0 (Vrchota et al., 2020; Singh et al., 2019; 2020; El-Gaafary et al., 2015; Chen et al., 2023; Anggoro et al., 2022; Heilala & Singh, 2023).

The EMS22 further examines the intricate dynamics between advanced manufacturing technologies and sustainability management systems. Through its indicators –from annual turnover, number of employees, manufacturing capacity utilization, return on sales, investments in machinery, annual payroll, and established year of factory (AT, NE, MCU, ROS, IEM, AP, and EYF) –Studies gain insights into how companies leverage technology and human resources differently. Particularly, the emphasis is on the effects of supply chain contract (SCC) types on various HR categories, from university professionals to trainees (Poloski Vokic & Vidovic, 2008; Puty, 2021).

However, the broadness of SCC and factory demographics has yet to lead to significant research maneuvers. The study establishes the manufacturing key enabling technologies (KETs) such as efficiency technologies and simulation, data analysis, and additive manufacturing (SDA) to find the relation for sustainability failure. These advanced manufacturing technologies are shaping modern manufacturing practices, making industries smarter and more efficient (Stanic *et al.*, 2018). The rise of AI and the potential integration of metaverse technologies further demonstrate within the orbit of the

industries (Lee *et al.*, 2022; Directorate-General for Enterprise and Industry 2009). The adoption of advanced manufacturing technologies has become a challenge. Firms that must catch up in innovation often find competing hard, indicating a pressing need for technological and human resource strategies to ensure sustainable growth. The role of HRM in moderating these transitions is critical, emphasizing the importance of training, competency development, and strategic HR practices (Vokic & Vidovic, 2008; Agudelo *et al.*, 2016; Piwowar-Sulej, 2021; Boehm *et al.*, 2021; Merriman, 2017; Hansen *et al.*, 2021; McCune *et al.*, 2006).

The research offers a multi-faceted understanding, suggesting that for Finnish industries to thrive, they must adopt technological advancements and sustainable human resource practices. This synthesis of past studies and the insights from EMS22 provides a holistic view of Finnish industries' current and future directions.

A. Research Issues and Hypotheses

This study seeks to understand the relationships and contexts of various DCES variables concerning SCC and HR classifications and their impact on Production Management/Control (PMC) efficiency, especially ET-based SDA technologies. The dependent technologies are computationally sustainable in considering waste integration between these (Yi, 2020; Jayanath & Achuthan, 2019). The system may follow certification. To this end, hypotheses were formulated and tested using a correlation model Eq. (1).

$$RHs = \begin{pmatrix} R_{1,1} & R_{1,2} & R_{1,3} & \dots & R_{1,21} \\ R_{2,1} & R_{2,2} & R_{2,3} & \dots & R_{2,21} \\ R_{3,1} & R_{3,2} & R_{3,3} & \cdots & R_{3,21} \\ \vdots & \vdots & \vdots & \ddots & R_{N,21} \\ R_{21,1} & R_{21,2} & R_{21,3} & & R_{21,21} \end{pmatrix} = 0$$
(1)

Noting hypothesized variables axioms (1) when the equation secondary latent (child) variables were 0 show no significant relation or not correlating (n.s./n.c.). On the contrary 1 indicates to satisfy, which is signified by asterisks in standardized 95-99.99% confidence interval tests. The hypotheses of (1) of the qualitative descriptive perspective are arranged as the DCES (AT, NE, MCU, ROS, IEM, AP, EYF)¹ is represented from the SCC (MFR, SPLR, CM)² perspective. How the operations performance qualifies in terms of HR^3 (graduates from universities/colleges, technically skilled workforce, technically or commercially trained force, semi-skilled and unskilled workers, and trainees in technical/industrial or commercial sectors, distributed within operations totaling approximately 100% impact. What performance extent, advanced manufacturing (PMC, ET & SDA)⁴ is implemented is explored in research radar:

 What is the influence of a company's descriptive¹ parameters on the adoption of advanced manufacturing⁴ techniques from the SCC² perspective? 2) How does a firm's HR³ background affect the adoption of advanced manufacturing³ techniques⁴ from the SCC² viewpoint?

These questions intend to examine the correlation between a company's performance metrics and the adoption of advanced manufacturing techniques, and how a firms' HR background impacts the adoption of these techniques during COVID-19.

II. RESEARCH METHODOLOGY

A. Industry Survey

1) Analytical approach

The study utilizes EMS22 results, focusing on Finnish EMS22 collected data from internet web portals, newspaper columns, and email newsletters. The respondents of the study are company managers or equivalent legal entities. The study adopted a multimethod approach centered on quantitative modeling to examine the distribution and dependencies of the variables. The method includes an embedded correlation model and a two-step process of quantitative data interpretation and merging to the literature perspective found (Scopus 26.6.2023.). The data analysis is based on multivariate tests. The objective is to understand how the variables.

2) Instruments used

The research tool was constructed based on the EMS22 model and implemented in Finland to foster corporatelevel discussions. This tool's data entries, or codings, broadened the DCES representation of the sampled companies from the manufacturer's perspective. The tool was designed to gather a spectrum of information, including Annual Turnover (AT, m23a1), Number of Employees (NEs, m23b1), Manufacturing Capacity Utilization (MCU, m23h), and Return-On-Sales (ROS, m23i1-m23i5), along with additional details like Investment in Equipment and Machinery (IEM, m23f), Average Payroll % of AT (AP%AT, m23g), and Establishment Year of the Factory (EYF, m23k). The measures defining the characteristics were linked to the viewpoint of the operators. These included the type of Supply Chain Contract (SCC) and whether the overall sample identifies as an operating Manufacturer (MFR, m03a1-m03a3), a Contracted Supplier (SPLR, m03a4m03a5), or a Contract Manufacturer (CM, m03a6). Labor Market performance within the organization is frequently distributed according to operation and qualification. Labor distribution is categorized as university/college Graduates (GUC, m16a1), Technically Skilled Workforce (TSW, m16a2), Workforce trained in Technical/Industrial or Commercial sectors (TF, m16a3), Semi-skilled and Unskilled Workers (SUW, m16a4), and Trainees in Technical/Industrial or Commercial sectors (TCT, m16a5). The complete organizational DCES, based on anticipated on-site characteristics, was subsequently matched with insights from KETs and OCs for manufacturing research. The study identified side effects such as the non-usage of

production management or control techniques within the organization and all companies adopting efficiency and SDA technologies. Hence, different entities were introduced for efficiency technologies (ET, m09k1–m09l1) and Simulation Data-Analysis and Additive (SDA, m09m1–m09p1) manufacturing methods, as well as Production Management or Control (PMC, m06f1–m06l1) (EMS, 2022). The DCES, SCC, HR, partial KETs, and OCs instrument variables were standardized into Z-score values and deployed into a statistical analysis program for social sciences. This programming technology examined resource reliability, combining subordinate variables into a single parent variable, and calculating arithmetic means to make the analysis interpretable. The analyses concluded as indicated by the protocol.

III. DATA ANALYSIS

A. Descriptive Statistics

Shared from the basic mathematics, the descriptive is said to provide the data depthness with its applications (Dong, 2023). Table I contains descriptive statistics of the measured variables, showcasing the range of responses from participants. Annual Turnover (AT) represents yearly revenue in millions of euros, whereas the Number of Employees (NE) refers to the overall workforce count. Manufacturing Capacity Utilization (MCU) denotes the utilization rate of main operations, while Return of Sales (ROS) is a value scale (from 1 to 5) representing profitability before tax. Additional parameters, namely Investment in Equipment and Machinery (IEM), Average Payroll (AP), and Establishment Year of the Factory (EYF), were included in the model. The DCES model necessitates the classification of Supply Chain Contract (SCC) type to define business segments (binary) as operating Manufacturer (MFR), Supplier (SPLR), or Contract Manufacturer (CM). Workforce categorization is important to understand internal labor distribution (summing to 100%). (EMS 2022).

For manufacturing, a specialized investigation introduced Key Enabling Technologies (KETs), including Efficiency Technologies (ET) and Simulation Data-Analysis and Additive (SDA) technologies. Organizational Concepts (OCs) latent variables covering Production Management or Control (PMC) were introduced, considering energy and environmental certifications considering controversies.

Starting from the DCES side, the sample consists of valid responses from 61 to 85 small-to-medium-large range corporations, according to AT and NE. MCU and ROS display statistical imbalances, requiring a more indepth correlation analysis for a comprehensive understanding. The descriptive statistics reveal a distributional skew, with the sample leaning towards a few larger enterprises amidst smaller ones. Regarding capital utilization, operations seem sustainable, but their competitiveness in fiscal year 2021 needs further examination. A qualitative analysis of Supply Chain

Contract (SCC) types showed 42% Manufacturers (MFRs), 14% Suppliers (SPRs), and 15% Contract Manufacturers (CMs) out of 87 valid responses.

Moreover, the workforce was comprised of 31% Graduates from universities/colleges (GUC), 23% Technically Skilled Workforce (TSW), 27% Technically or Commercially trained Force (TF), 17% Semi-skilled and Unskilled Workers (SUW), and 3% Trainees in Technical/Industrial or Commercial sectors (TCT), totaling approximately 100%. The research highlighted that not all companies use a specific range of production management/control methods.

TABLE I. DESCRIPTIVE STATISTICS	(EMS 2022 RESULTS)
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AT21 0	339 326	26.219							VALID	
ATT10 0	326		6	1	52.445	3.767	17.641	2071.329	79	
A119 0	520	24.84	6	1	52.661	3.8716	17.471	1912.7	77	
NE21 3	600	84.000	40	12	115.41	2.335	5.980	7140	85	
NE19 2	500	78.229	40	6	105.79	2.1043	4.249	6493	83	
MCU21 0	100	66.672	75	80	28.975	-1.227	0.664	4267	64	
MCU19 0	100	63.295	75	0	31.812	-0.907	-0.34	3861	61	
ROS 1	5	3.423	4	5	1.567	-0.509	-1.290	267	78	
IEM 0	65	4.975	0.131	0	12.72	3.332	11.220	323.37	65	
AP 0	2	0.395	0.3	0.2	0.362	2.732	10.048	26.476	67	
EYF 2	104	29.013	25	5	21.398	1.399	2.604	2292	79	
MFR 0	1	0.423	0	0	0.496	0.317	-1.931	52	123	
SPR 0	1	0.138	0	0	0.347	2.123	2.546	17	123	
CM 0	1	0.146	0	0	0.355	2.026	2.139	18	123	
GUC 0	100	30.980	20	10.0	29.351	1.056	0.109	3779.605	122	
TSW 0	100	22.561	15	0	22.731	1.388	1.424	2752.393	122	
TF 0	93	27.393	20	0	25.478	0.724	-0.516	3341.922	122	
SUW 0	100	16.546	5.000	0	24.040	1.591	1.533	2018.668	122	
TCT 0	15	2.501	0.000	0	3.555	1.348	1.051	305.120	122	
ET 0	1	0.276	0.000	0	0.3798	0.959	-0.597	34	123	
SDA 0	1	0.341	0.200	0	0.3185	0.641	-0.672	42	123	
PMC5 0	1	0.49	0.00	0	0.502	0.049	-2.031	60	123	
PMC6 0	1	0.15	0.00	0	0.363	1.936	1.776	19	123	

TABLE II. CONSTRUCT CORRELATIONS (EMS 2022 RESULTS)

		0	0	-		,		0	0	10	11	10	10	14	15	16	17	10	10	20	01	00	00	0.4
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
AT21	1																							
AT19	.991	1																						
NE21	.818 ****	.807 ***	I																					
NE19	.822 ****	.831 ***	.983 ****	1	_																			
MCU21	.243 *	.267 **	.131	.123	I																			
MCU19.	.245 *	.244 *	.209	.195	.829	1																		
ROS	.233 **	.221*	.221*	.203 *	.300 **	.241*	1																	
IKM	.398 ***	.404 ***	.265	.307	.002	021	.214 *	1																
AP	338 ***	283	274 ***	297	163	3/8 ***	112	072	1															
EYF	.149	.147	.270 **	.317 ***	.146	.212	.129	.548 ****	407 ***	I														
MFR	122	135	147	149	.217*	.077	.184	.097	093	.175	1													
SPR	077	069	.006	.013	083	008	276**	106	.203 *	226 **	343	1												
CM	038	051	048	-41	.102	.194	.031	09	153	.101	354	-0.166 *	1											
SCC	208*	22*	-162	-151	.202	.231*	058	095	02	.034	.268 ***	.435	.425	1										
GUC	044	001	036	016	319 **	393 ***	250 **	.043	.491 ***	237 **	-238 ***	.391	217 "	06	1									
TSW	047	066	.15	0	.192	.162	.083	065	207 -	-117	.1/2-	12/	004	.036	359	1								
TF	.056	.065	01	.001	.183	.244 -	.014	002	149	.125	066	122	.138	04	411	-2/3	1							
SUW	0	044	.11	012	.023	.094	.235	.013	324	.293	.212	220	.087	.069	429	201	293	1	,					
ICI III	.285	.260 **	.221	.215	.022	.018	.201-	.012	064	.108	-103	057	.246 ***	.077	119	112	056	.163	1	,				
HK III	.2/1	.236 **	.217	.206 -	.1	.112	.257	005	192	.145	024	148	.2/5	.091	350	.066	035	.265	.966	1				
E1 (7)4	.295	.306 ***	.298 ***	.311	.042	075	.062	.227 -	134	.161	038	13/	.123	05	214	036	03/	.311	.154 -	.197	422 ##	1		
DMCE	.1/3	.190	244 ***	276 ***	.045	.011	009	.034	042	540 ****	008	240 ***	.002	.047	205 **	055	108	.107	.107	.14	.433	211 **	т	
TMC5	262 ****	200 ****	475 ****	510 ****	204	.055	102	.213	189	152	.133	249	.030	04	205	.004	120	.220	.100	.15	162 *	2211	202 ***	1
PMCO	.303	.300	.4/5	.516	.200	.11	.105	074	25	.155	.044	.024	-115	04	065	.055	.156	099	.044	.00	.105	.221	.393	1 DM/O/
	AIZI	A119	NEZI	NE19	MCU21	MCU19	RUS	IEM	AP	EIF	MFR	SPK	CM	SCC	GUC	15W	11	SUW	ICI	нк	EI	SDA	PMC5	PMC6

B. Study Methodology: Correlation Modeling

Pearson's correlation (R) is employed to assess the correlation between DCES and KETs parameters of interest (Table II). This metric quantifies the degree to which two variables vary together. Pearson R was chosen to elevate Type I error rates (Bishara & Hittner, 2012), thereby facilitating clearing outlier extraction. The method can assess the strength of linearity between two variables to indicate non-linearity (Bishara & Hittner, 2012). This correlation coefficient was used to maintain a larger sample size and optimize empirical considerations (Graf & Bauer, 2011).

Bartlett's sphericity test revealed an acceptable score for model factors, an appropriate determinant, and an adequate Kaiser-Meyer-Olkin measure. Despite these acceptable parameters, the observations from the descriptive statistics point out that the data may only be suited for some models. However, this does not necessarily invalidate hypothesized correlations. Therefore, a pairwise investigation approach will be utilized.

With focus for correlation, the investigation of is shown in Table II. Though the data distribution appears skewned, the normalized distributes along with the central limit theorem. This asserts when sample size increases, the sampling distribution of the mean tends to normalize, irrespective of the original population distribution's shape (n > 30/40).

Given the complexity of the dataset from the supplier's viewpoint, understanding the results require focused

interpretation. The findings are based on the two formulated research questions.

Regarding Research Question 1, the analysis points out that small to large companies (in the sample's scale) within the sample maintain high competitiveness, demonstrated by ROS. Notably, older companies established for longer tend to have higher investments and display a greater degree of competitiveness than newer counterparts. Furthermore, smaller companies excel in managing their operational costs, which leads to higher MCU rates and ROS relative to their AT. While demonstrating similar competitiveness, larger companies make more substantial investments (larger working capital). Additionally, between the years 2019 to 2021, a technological shift occurred within the sampled companies, adopting advanced technologies such as something from the SDA portfolio, leading to improved growth and operational efficiency. It is interesting to note that the data shows a higher growth percentage for companies that have adopted these technologies, emphasizing the critical role that technology adoption has in driving business growth.

Regarding Research Question 2, from an HR perspective, there is an apparent demand for trainees within manufacturing companies. Companies that manage operational costs effectively often employ more interns, potentially signifying their success and readiness to incorporate new hires into operations. However, there is also a significant need within many manufacturing companies for a workforce educated at the university level to increase their capacity for innovation in advanced manufacturing technologies. Furthermore, the analysis indicates that older companies sustain operations when AP costs are approximately less than ROS. This balance is key to maintaining sustainable operations and often necessitates the implementation of advanced technologies.

IV. CONCLUSION

The study findings show the key factors regarding supply chain contract type for structure and adoption of advanced manufacturing technology and practices contemplated in the DCES of the sample. It underscores the increased adoption of efficiency, simulation data analysis, and additive manufacturing technologies among the most competitive firms during 2019-2021. It also highlights the influence of energy management systems on companies' cost structures and resilience to energy market volatility. Interestingly, firms leveraging cost-effective technology for self-reliance demonstrate a higher level of innovation and a larger number of trainees, indicative of sustainable operations. However, the study also reveals uncertainty within the industry, such as uneven efficiencies in response to resource-saving and production and a decrease in the variation of university/college graduates among associated companies. These findings underline the need for a more in-depth exploration of these dynamics' implications on the industry's future trajectory.

Future research evidence is optional to understand the determinants of competitiveness within the Finnish manufacturing sector's lack of technology adoption with workforce composition, energy management, and

environmental certification. There is a need for objective longitudinal studies to track the evolution of these trends. The long-term impact on the industry's competitiveness and sustainability can be scoped from EMS22 by partnering with respondees to deploy certifications related to tenders' integration, perhaps as a new requirement. It is beneficial to implement cross-country comparisons. The path analysis of the relationship between company size, technology adoption, competitiveness, and the role of an educated workforce in promoting innovative practices and sustainability is beneficial because the respondents' success is only partially visible.

V. CRITICISM AND FUTURE RESEARCH PREDICATIONS

There is all novel in this study. This has implications for understanding the narrowness of advanced manufacturing in additive and efficient domains. At the same time, successful simulation and data analysis-based actions are rare within the sample with certifications in environment and energy. However, it is unethical to cherry-pick the results without referring to the full context: This study cannot be generalized and has implications for the micromanagement of the circle of respondees and, in the future, in terms of improvement. Research may be open to future cooperation and new partnerships outside Europe for comparison.

CONFLICTS OF INTEREST

The authors have no conflicts of interest to disclose.

AUTHOR CONTRIBUTIONS:

Heilala was instrumental in the comprehensive execution of this study. Heilala collected the data, conducted a thorough analysis, produced illustrative figures, and composed the manuscript; Kantola contributed significantly by providing insightful comments and suggestions that enhanced the quality and clarity of the research work; the authors reviewed and approved the final version of the manuscript.

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