TURUN YLIOPISTO
UNIVERSITY OF TURKU

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ABSTRACT

This dissertation investigates the complex factors shaping the future of manufacturing, focusing on innovation, competitiveness, and employment trends within the European context. Leveraging the extensive 2022 European Manufacturing Survey dataset, it models relationships between critical technological and organizational variables impacting manufacturing resilience using cross-lagged panel path analysis. Against the 2019–2021 economic and environmental backdrop, the research examines manufacturers' integral survival strategies derived from challenges faced. Factors like business innovation models, organizational concepts, key technologies, and relocation approaches are assessed for performance. The study reveals competitive standards: automation, robotics, additive manufacturing, access-based business models, maintenance services, and production organization. These discoveries have profound implications for enabling the transition to next-generation sustainable manufacturing through technology integration frameworks. The research marks the need for investments in cross-sectoral research coordination. As climate change intensifies, reimagining manufacturing is critical. While acknowledging limitations like sample size and scope, the dissertation offers a detailed understanding of the manufacturing system's components and the relationships of success, forward strategies, and human-technology-environment interlinkages. This multidimensional perspective provides insight to catalyze the creation of integrated manufacturing ecosystems worldwide.

KEYWORDS: manufacturing, technology, organizations, strategic relocation, conceptual model philosophy, experimental structural equation modeling

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TIIVISTELMÄ

Tässä väitöskirjassa tutkitaan valmistusteollisuuden tulevaisuutta muokkaavia monitahoisia tekijöitä keskittyen innovaatioihin, kilpailukykyyn ja työllisyyden kehityssuuntauksiin eurooppalaisessa kontekstissa. Siinä hyödynnetään laajaa vuoden 2022 European Manufacturing Survey -aineistoa ja mallinnetaan valmistusteollisuuden joustavuuteen vaikuttavien kriittisten teknologisten ja organisatoristen muuttujien välisiä suhteita käyttämällä ristiin viivästettyä paneelipolkuanalyysiä. Vuosien 2019–2021 talous- ja ympäristökehitystä vasten tutkimuksessa tarkastellaan valmistajien kokonaisvaltaisia selviytymisstrategioita, jotka on johdettu kohdatuista haasteista. Suorituskyvyn kannalta arvioidaan sellaisia tekijöitä kuin liiketoiminnan innovaatiomallit, organisaatiokonseptit, avainteknologiat ja siirtämistavat. Tutkimus paljastaa automaation, robotiikan, lisäainevalmistuksen, pääsyyn perustuvat liiketoimintamallit, kunnossapitopalvelut ja tuotannon organisoinnin kilpailustandardeiksi. Näillä löydöksillä on syvällisiä vaikutuksia seuraavan sukupolven kestävään valmistukseen siirtymisen mahdollistamiseen teknologian integrointikehysten avulla. Tutkimus osoittaa, että tarvitaan investointeja tutkimuksen monialaiseen koordinointiin. Ilmastonmuutoksen kiihtyessä valmistusteollisuuden uudelleenkäsittely on ratkaisevan tärkeää. Väitöskirja tarjoaa yksityiskohtaisen käsityksen valmistusjärjestelmän osatekijöistä ja menestyksen, edistysstrategioiden ja ihmisen, teknologian ja ympäristön välisten yhteyksien välisistä suhteista, vaikka siinä tunnustetaankin otoksen koon ja laajuuden kaltaiset rajoitukset. Tämä moniulotteinen näkökulma tarjoaa näkemyksiä, joiden avulla voidaan edistää integroitujen valmistusekosysteemien luomista maailmanlaajuisesti.

ASIASANAT: valmistus, teknologia, organisaatiot, strateginen toimipaikan muutos, käsitteellinen mallifilosofia, kokeellinen rakenneyhtälömallinnus

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List of Original Publications

This dissertation is based on the following original publications:

I Heilala, J., Salminen, A., Bessa, W. M., & Kantola, J. (2023a). Optimizing smart factories: A data-driven approach. Global Journal of Researches in Engineering: G, Industrial Engineering, 23(3), ICIE 2. Global Journals Inc. http://dx.doi.org/10.34257/GJREGVOL23IS3PG15 Publication Forum Level 0.

II Heilala, J., Bessa, W., Kantola, J. & Salminen, A. (2023b). An exploratory analysis of supply chain contracts on efficiency, simulation, and data analytics augmentation technologies. Journal of Advanced Management Science (JOAMS) Open Access. Publication Q1/2024. 12(1), 8-13. https://doi.org/10.18178/joams.12.1.8-13 Publication Forum Level 0.

III Heilala, J., Bessa, W., Kantola, J. & Salminen, A. (2023c). The exploratory impact of technology, organizational concepts, and employee training on business performance. Journal of Economics, Business and Management (JOEBM) Open Access. Publication Q2/2024. Publication Forum Level 0.

IV Heilala, J., Kantola, J., Salminen, A., & Bessa, W. (2022c, December). Relocation activities for the development of employment and competitiveness situations. In 1st Australian International Conference on *Industrial Engineering and Operations Management*. Australia, Sydney 16-18.12.2022. https://doi.org/10.46254/AU01.20220642. Publication Forum Level 0.

V Heilala, J., Krolas, P. & Gomes de Freitas, A. (2023d). Advanced engineering management based on intersectional R&D challenges on education: a case study for product classifications on shoring trends. *Human Factors in Design, Engineering, and Computing* with Taylor & Francis. Publication Q1. 2024 Publication Forum Level 0.

The inspiring preliminary conferences are represented on pages 14–16.

Author Contributions

Janne Heilala: Original text preparation: conceptualization, methodology, investigation, data curation, formal analysis, writing. (I, II, III, IV, V).

Jussi Kantola: Supervision: Review comments (I, II, III, IV).

Antti Salminen: Supervision

Wallace Bessa: Supervision

Pawel Krolas: Review comments. (V)

Andrea Gomes de Freitas: Review comments. (V)

1 Introduction

Innovation models and digital services require prominent research features to clarify digital vision objectives for industry development. Current research necessitates deep analysis with theoretical support to develop industry structure, partially for business safety and confidentiality reasons, as business secrets are more difficult to disclose in collaborative research reliant on vital functions (Hautala-Kankaanpää, 2023; Hyvönen et al., 2023). Research distribution across time domains should emphasize contributions, not exacerbating manufacturing competitiveness or supply chain gaps. This dissertation combines the European Manufacturing Survey (EMS) 2022 exploratory studies to contribute to Finnish manufacturing's global innovation competitiveness forefront. Exploratory data analysis processed for journal writing showcases sample entries with theory-driven hypotheses based on exploratory results, perhaps visibility-latent, granting corporations a competitive advantage to create beneficial customer-cost activities with technology (Manthey et al., 2022). There are ways to investigate technological innovation, success factors for adopting brilliant manufacturing transformations measure hindering production innovation on intelligent systems, information management systems, and in-house versus outsourcing considerations (Jung et al., 2023; Won & Park, 2020). Information management systems signify substantial investment decisions with benefits. Smart manufacturing data-information-knowledge innovativeness cannot be understated, as it directly shapes strategies (Kim et al., 2023) through organizational structures determining digital technology integration depths into industrial processes.

This thesis focuses on EMS-collected innovation and technology management implications to understand industry sector competitiveness and employment development. Rare data availability rationalizes investigating management advanced manufacturing innovation investments—publication-level technological measurement positions into a Fraunhofer Institute for Systems and Innovation Research Finland project. Online CEO-distributed, organization-reflective EMS data per a Consortium for European Manufacturing Survey 2022 (EMS22) coordinated by the Institute for Systems and Innovation Research assembled the survey to comprehensively capture 2019-2021 manufacturing organizational states (Heilala, 2023a).

Combining EMS22 respondent structural element inputs formed a multifaceted investigation. This thesis supports an integrated industry perspective in assessing factors contributing to ongoing Industry 4.0 discourse value from research professionals to business owners. Key focus areas have included digitalization strategy integration into Industry 4.0 for light generalization sample saturation since competitiveness and investment potential decreases seen since the 2009 economic crisis recovery—unique EMS pandemic measurement interval comparisons evidence business sustainability as a discussion topic. Industry 4.0 strategy changes signal future transformations (Kaivo-oja et al., 2018). Improved from 2009 EMS, EMS22 focuses on innovation with cybersecurity, connectivity, autonomous and computer vision production management, emphasizing high technology efficiency (Heilala et al., 2023a). University and research laboratory collaborations concentrating on energy, reliability engineering, and logistics improve returns (Kaivo-oja et al., 2018). In turn public-private partnerships across sectors focusing on efficient energy technologies present high-technology adoption opportunities (Pinilla-De La Cruz et al., 2022).

The EMS sample increasingly focused on responding to their sustainable practices for improved manufacturing efficiency, which could be seen from techno-organizational greenhouse gas emission reduction and efficiency improvements from a sustainability perspective (Mattila, 2021). Global customer considerations drive firms' advanced manufacturing repositioning potential within additive manufacturing, strengthening supply chain resilience programming currently supports the resilience framework. Inspiring public-private partnership programs could serve labor productivity gains as manufacturing outages decline. Competitive investing companies undergo productive transitions, upholding Finnish responsibilities during traditional manufacturing decline. Intergenerational lifecycle thinking sustainable development goals lead to governmental efforts to improve traditional manufacturing (PMO, 2020).

This EMS22-studied book provides a traditional manufacturing counterpart with a sustainable development angle, offering strategies and action plans to progress beyond Industry 4.0. Recommended patterns of employee migration to manufacturer characteristics in Finland rely heavily on quantitative measures like employee numbers and turnover in defining SMEs. Critical consideration of qualitative industry-specific growth and managerial capacity factors enables a more accurate understanding of SMEs (Stat, 2023).

Structured content progression begins with an introduction of each component of EMS22, encompassing theoretical frameworks through hypothesis formulation, and transitions methodology from employed methods to data processing techniques. Analysis modeling and interpretation set the stage to examine recommendations for a randomly selected study sample regarding digital transformation-necessitated future organizational and managerial adaptations. Crafted segments underscore the importance of interdisciplinary collaboration, exemplified in standardized customer relationship management development within Manufacturing-as-a-Service (MaaS) contexts (Pessot et al., 2021). MaaS links to evolving operations management responsibilities.

Operations management recommendations include scrutinizing bankruptcy costs, tax shields, order integrity, and agency/signaling roles within international trade classification-level capital structure decisions. This incorporates the Heilala et al. (2023d)-cited Heilala and Krolas (2023)'s set sustainability standard. Other adaptations from Norton (1990) include investments for managerial discipline, ownership, and equity investment-product manufacturing-sales operations dynamics analyses.

Among other firms, manufacturers were a "scarce resource" in some regional industry horizontals, potentially affecting more horizontal research needs (Hogeforster & Wildt, 2021). European SME numbers were 228,562 in 2019; new companies fulfill ~75% of demand, more significant in different areas, justifying horizontal movement (Hogeforster & Wildt, 2021). Figure 1 shows the demand for SME cross-Europe business development roles.

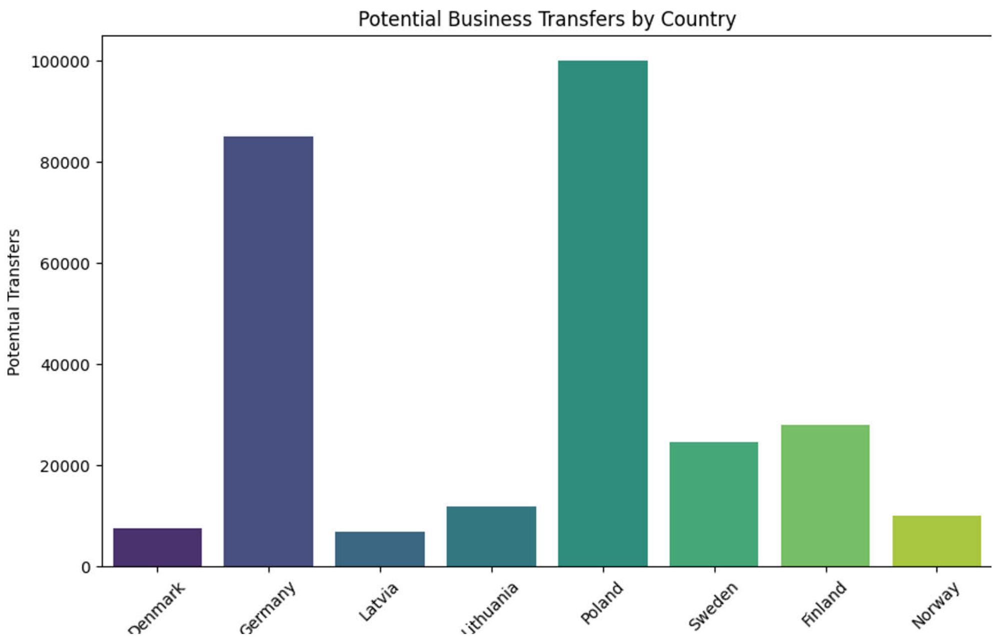

Figure 1. Depicts yearly techno-organizational firm transfers in Europe, highlighting Poland and Germany's significant potential due to their large firm counts (Hogeforster & Wildt 2021).

Transfers of techno-organizational capabilities between firms have significant potential to facilitate economic stability and growth in European countries (Hogeforster & Wildt, 2021). As Hogeforster and Wildt (2021) show, countries like Poland and Germany demonstrate high levels of potential for such transfers, with large numbers of firms (p. 1–32). These transfers help maintain regional competitiveness, while strategic management of transfer processes also affects business sustainability. Key metrics include the proportion of SMEs in each country, contributing innovation, and measurements of total demand for entrepreneurs compared to the proportion fulfilled by firm transfers (Hogeforster & Wildt, 2021). Though not a direct measure, the EMS22 provides a useful proxy indicator of potential techno-organizational development through firm transfers dominated by manufacturing. It points to substantial unfulfilled transfer needs, suggesting a technology vacuum necessitating strategic business response (Hogeforster & Wildt, 2021; Varanka et al., 2021).

The industry has shifted significantly during the global pandemic, bringing new challenges and opportunities for firm transfers and adopting updated, sustainable competencies (Hogeforster & Wildt, 2021; Heilala et al., 2023c). The financial sector has also adjusted, improving resilience in response to crises and reforms (CGFS, 2018). Modeling by Heilala et al. (2023c) predicts that controlling the pandemic's progression has more significant economic benefits than the costs of restrictive policies in Western countries. Investments have had some direct positive competitiveness impacts. Careful statistical noise management in the EMS22 avoids uncontrolled escalation of epidemic impacts, minimizing negative consequences (Varanka et al., 2021). EMS22 demonstrates intense statistical rigor under examination, with thorough meta-level and residual analysis (Draper & Smith, 1998; Kutner et al., 2004; Weisberg, 2014; Fox, 2016).

Specifically, the pandemic initially caused order decline and disrupted supply chains across industries like manufacturing (Malgorzata, 2021; Heilala et al., 2023c). However, it also conditioned expanded adaptability, shifting firms towards resilience for circular economy (Heilala et al., 2023c). SMEs similarly demonstrated adaptability amidst the challenges of maintaining costs while refocusing business direction (Wiardi & Saputra, 2022). Circular economy approaches have also drawn increasing interest as a sustainability strategy since 2019 (Tura et al., 2019).

The policy has responded through renewable energy subsidies and infrastructure investment tenders, helping achieve Western decarbonization targets, like carbon neutrality, by 2035 (Businee Finland, 2023). Sustainable manufacturing and circular economies are crucial for waste-driven industry transformation towards these goals (Urbinati et al., 2020). While scaling sustainable manufacturing has had technical, integration, design, capability, and financial barriers, most businesses must now pursue decarbonization within ten years (Deloitte, 2019; Accenture, 2023). Artificial intelligence is expected to assist the urgent transition (Accenture, 2023).

1.1 Research purpose

This study provides comprehensive illumination of the impacts of techno-organizational practice, focusing specifically on crucial manufacturing technology enablers within the EMS scope. As the view narrows between competitiveness, employment situations, enabling key technologies, organizational concepts, and relocation activities across the European Finnish territory, the dissertation objectives were to determine the complete structural validity of techno-organizational relocation practices; Strategic advantages of technology development on offshoring manufacturing; Firms' opportunities to embrace advanced engineering design research (Heilala, Krolas & Gomes de Freitas 2023). To this end, a framework was obtained from Scopus. Ensuring academic thoroughness, this dissertation incorporates inspirational insights from various scholarly interpretations. Generally, scoping reviews showed growth in popular research domains, while Scopus-literature analysis demonstrated expanding studies across enabling sectors, facilitating rigorous integration (see Figure 2).

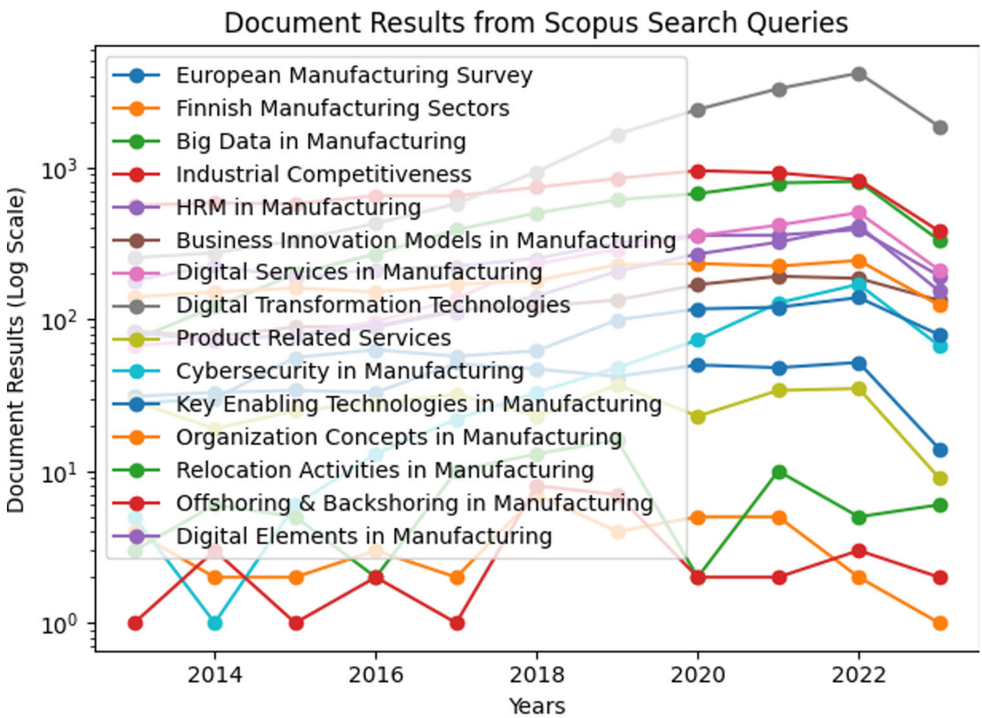

Figure 2. Manufacturing technologies applications increasing trends in logarithmic scale with given keywords to the Scopus database. (2013–2023).

The research framework needs to be centered on manufacturing technologies at the depth of the engineering variables provided. The scope of the EMS is political, while the research scope of politics and business to ensure academic thoroughness purpose for future manufacturers' education, coded in the EMS (2022) domain, as improved within the dissertation context. Content links through journal articles (JA1-3), a book chapter (BC), and conferences (C1-6), delineating the scope per Figure 3.

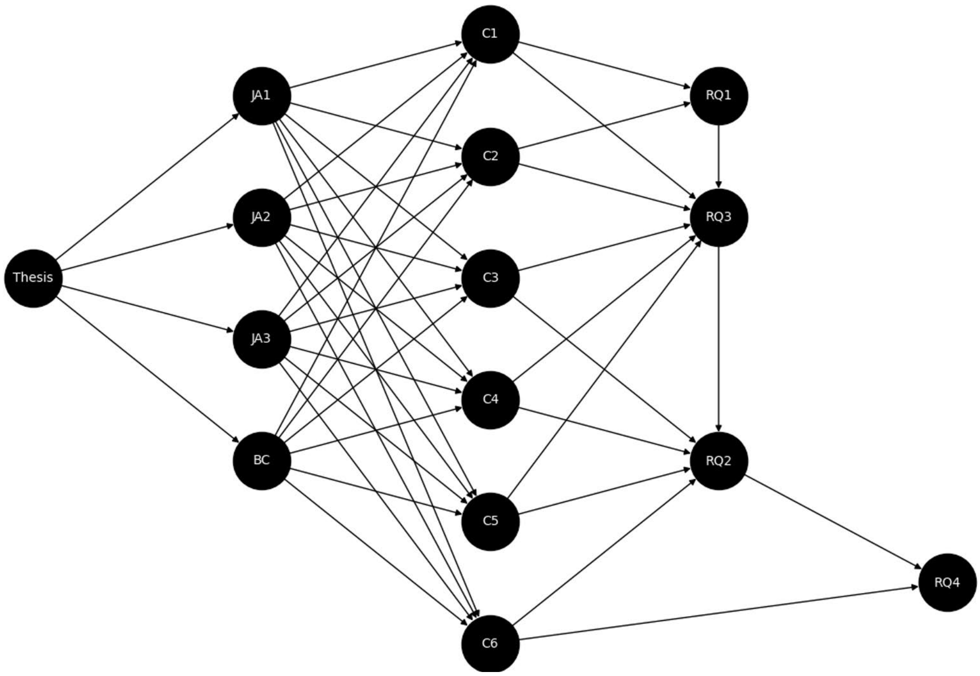

Figure 3. Shows supply chain contract networks, centered on Heilala's 2022 global management strategy. It connects various topics: competitiveness (C2), organizational concepts (C3), relocation (C4), and manufacturing management (C5, C6), along with other journal articles.

1.2 Research questions

The manufacturing sector remains a critical driver of the global economy, witnessing rapid technology adoption and evolving organizational practices that enhance competitiveness and drive employment growth. This has given rise to a "manufacturing metaverse" - an integrated digital ecosystem enabling unprecedented innovation, collaboration, and growth opportunities (Heilala, 2023d; Heilala & Singh, 2023).

Developing research questions (RQs) to model the complex relationships within this metaverse formed the foundation of this study. The aim was to examine the links between key technological factors, organizational concepts, and their impact on competitiveness and employment trajectories. Given the transformative and rapidly evolving nature of digital age manufacturing, modeling these technology-organization-performance connections is indispensable.

The RQs were framed against a backdrop of innovation, with a focus on emerging digital process control and advanced production technologies. Ensuring resilience through robust cybersecurity, efficient production management, and strategic relocation capabilities was a prime consideration in this dynamic manufacturing landscape.

The central RQ examined: What technological integrations and firm characteristics influence competitiveness and employment growth within the 2019-2021 Finnish manufacturing sample studied?

Subsequent analysis by Heilala et al. (2023a, 2023b, 2023d) on study validity raised points regarding the findings' usability, which can be explored through the following specific RQs:

RQ1:

- What are the critical technological enablers for improving factory floor operations, and how do different technologies like automation, robotics, production control systems, and additive manufacturing impact manufacturing performance? (Based on Heilala, 2022; responsively Heilala et al., 2022a).

RQ2.1–2:

- How do the organization of production processes and investments in training/competency development influence a firm's competitiveness and employment levels? (Based on Heilala, 2022; responsively Heilala et al. 2023a)
- What is the role of decision-making related to manufacturing education/training in areas like automation and robotics? (Linking to RQ1)

RQ3:

- How can firms position themselves at the frontier of intelligent manufacturing through strategic investments in R&D, ecosystem collaboration, multi-material capabilities, and data-driven additive manufacturing technologies? (Based on Heilala et al. 2023bc responsively Heilala, Krolas, and Gomes de Freitas 2023d;)

RQs delineate a network of connections from a supply chain contract perspective. Conference proceeding C1 on deploying competitive techno-organizational global supply chain management (Heilala, 2022) to the complete thesis broad show example preliminary framework to C2 exploring developing competitiveness and employment situations regarding key manufacturing technologies at whole depth (Heilala et al., 2022a). C3 examines manufacturing organizational concepts similarly (Heilala et al., 2022b), while C4 discusses relocation activities (Heilala et al., 2022c) with (Heilala et al., 2023d) as of search for technologies for advanced manufacturing capabilities should foster mitigation of sea level rise (Heilala et al., 2024). The complete lifecycle manufacturability of complex platforms, in turn, investigates the manufacturing management of C5 in terms of climate change issues (Heilala & Krolas, 2023; Heilala et al., 2023d), and C6 examines integrating additive manufacturing systems on Heilala Parchegani Chosaki & Piili (2023) supporting the research. These conferences provided foundational inspiration for several original publications. These dissertation JAs (journal articles) include JA1 on complete view of digital competitive advantage in Industry 4.0 (Heilala et al., 2023a), JA2 analyzing supply chain (Heilala et al., 2023b), JA3 examining technology, organizational concepts, and training on performance (Heilala et al., 2023c), and BC (book chapter) on advanced engineering management challenges interconnected to product classification shoring trends were introduced closely (Heilala et al., 2023d). Due to industry limitations, adaptability is essential (Philbeck & Davis, 2018). This monumental manufacturing technological growth period makes this research both timely and crucial.

1.3 Research approach

In this chapter, empirical research investigating an integrated theory of sustainable manufacturing is presented. The comprehensive approach analyzes how various digitalization factors and key techno-organizational enablers contribute to sustainability within the manufacturing sector. A space of fundamental questions is employed with an a priori model, the Development of Competitiveness and Employment (DCES) model, to measure the impact of manufacturing digitalization for RQ1 performance, RQ2 education and RQ3. The DCES model incorporates several critical elements from the European Manufacturing Survey (EMS), including key enabling technologies (KETs), organizational concepts (OCs) for relocation activities, digital services (DSs), and cybersecurity practices (CPs). These elements are evaluated through the lenses of supply chain contracts (SCCs) and human resources (HR). By examining these factors, the driving forces behind competitiveness and employment in specific areas are elucidated, ultimately emitting light on their influence on the overall sustainability of manufacturing systems. Figure 4 visually represents this integrated theory of sustainable manufacturing, modeling how the digitalization variables and key techno-organizational enablers contribute to sustainability. The figure provides a comprehensive overview of the intricate relationships and dynamics radiating within the theoretical framework.

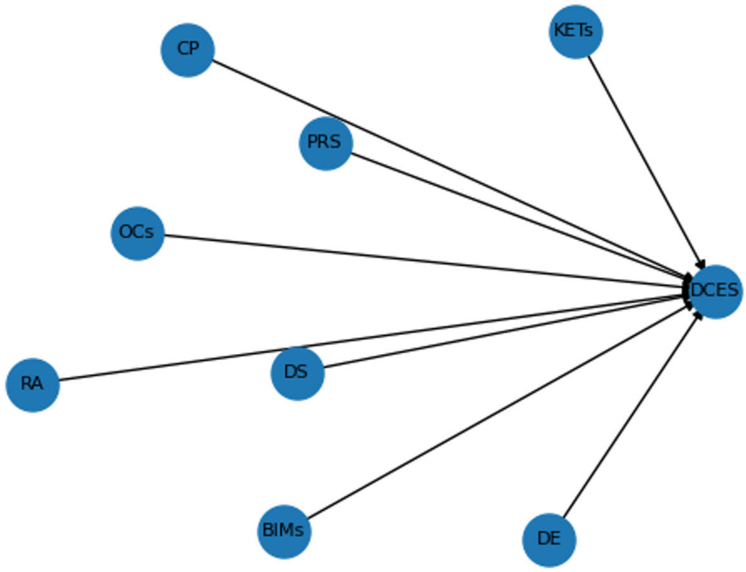

Figure 4. A priori DCES model links manufacturing digitalization, relocation, digital services, cybersecurity, to competitiveness and employment. (Heilala et al., 2023a.).

Following a digital manufacturability strategy with distributed systems has taken higher frequency (Teece, 2018) toward African solicitation tendering. Recent research found associated concepts permeating organizations revolving around the digital revolution (Thun et al., 2019). Figure 4 symbolizes a revolution of factors, with a priori forms expecting the benefits of selective sustainable manufacturing practices. Sustainability search significantly enables competitiveness and employment interdependently within firms, subject to development in validation (Heilala et al., 2023a). This a priori framework focuses on modeling the sustainable development of competitiveness and employment. Broader theoretical exploration also suggests investigating sustainability lifecycle manufacturing interactions for improving manufacturing conditions (Casamayor et al., 2023; Fatais & Karwowski, 2023 (Heilala (2023d) cited Heilala & Singh (2023).).

Perspective aligns with embedded systems operations (O3D, 2022), qualitatively assessing technology, practices, and resilience. The explicit technological role in past research regarding technologies for supply optimization is under investigation (Alsolbi et al., 2023). Additive innovation opportunities can provide environmental, financial, and social benefits supporting circular economies and fossil freedom (Brauers & Oei, 2020). Techno-organizational forming (Li et al., 2018; Reig, 2023), data security (Alsolbi et al., 2023; Bayat et al., 2023), and employee capital utilization (Tofail et al., 2018; Burnside, 1995) continuously in place for updated scope for research. Key manufacturing technologies can positively influence competitiveness and employment (Heilala et al., 2023ac).

Introduced business adaptability, aligning with Industry 4.0 reconfiguration (Philbeck & Davis, 2018), which aligns with the implementation of the manufacturing research, is essential. The hypothesis tests the dependence between competitiveness, employment, and factors like contracts, resources, technologies, concepts, activities, practices, services, and innovation models. At the same time, this dissertation evaluates the visible validateable spectral wavelengths of how configurable the manufacturers' perspicuity is (Heilala et al., 2023ac).

1.4 Historical studies and the study

Historical studies show the details of manufacturing economic turbulence (Kinkel et al., 2015). By 2019, multifaceted events triggered urgent sustainability imperatives: the EU's declared climate crisis and pandemic mobility restrictions severely disrupted operations and insolvencies (OECD, 2021). Amidst the 2019-2021 socioeconomic vortex, what strategies did resilient manufacturers use to withstand challenges? Impacts differed, requiring decoding success factors within this horizontal. Given Finland's digitalization leadership, exploring manufacturer perspectives is needed to gain depth in particularly digitized manufacturing.

The manufacturing sector contends with increasing global competition and rapid technological change, necessitating continuous innovation for competitiveness. Thus, this study leverages EMS22 data encompassing supply chain, human resources, innovation models, and other quantified concepts to model industry development and competitiveness (EMS, 2022). The focus is on innovatively integrating and aligning literature concepts with these unexplored research avenues.

Competitiveness impacts differ regarding capital utilization, with employment connections seeing only partial productivity spectrum sensitivity (De Lima et al., 2023). Sustainability necessitates lifecycle production analysis for growth and is a cornerstone for sustainability facets (Machek & Machek, 2014). Rising efficiency reliance heightens this assessment's criticality amidst efficiency requirements (European Commission, 2019). Innovative systems change management requires financial support for intelligent systems development (Brzezinski & Wyrwicka, 2022). Western 2030 strategic pollution and 2050 resilience targets require the participation of the private sector to reach zero emissions (European Commission, 2022a; Business Finland, 2022). Discussing intelligent manufacturing solutions for raising efficiency and energy savings aligns with these goals. The global crisis creates opportunities for efficiency rethinking.

1.5 Positioning the establishment of framework

Empirical investigations found that digitalization has not directly decreased corporate employment; automation costs pose challenges requiring innovative job creation. Studies show digital systems shaping daily lives and employment through new organizational structures (Jäger et al., 2015, 2016). Digital transformation enables real-time communication to enhance responsiveness and reduce latency, sparking organizational learning innovation using intrinsic and extrinsic performance-linked resources (Roco & Bainbridge, 2003; Eke et al., 2020). Automating virtual systems increases profitability over manual process costs and yields. Innovation also drives offshoring when domestic resource costs are higher, though growth companies often start locally (Jäger, 2016; Teece, 2018). Strategies for reliable competitiveness and employment measurement have significant historical model leadership for innovation (European Commission et al., 1994).

Outsourced innovation allows for acquiring competitive assets externally as a secondary entity (Faullant & Knudsen, 2019). The innovation process involves ideation, brainstorming, opportunity identification, refinement, and implementation based on work orders and objectives (Apilo & Taskinen, 2006) that can be fully automated with generative artificial intelligence set open and transparent boundaries. This forms space for sustainable development within Industry 4.0, governing metrics to transition towards environmental protection and post-industrial green society (Morelli et al., 2022). Similar protocols improve traditional business operations and delivery (Kallonen et al., 2021). Pillars ensuring profitability through transactions, incentives, and investments also indicate innovation sustainability (IAEA, 2008).

1.6 Manufacturing efficiency target variables research design

Production, outcomes, control variables, and information interact deductively and mutually (Subramaniam, 2020). These integrate efficiency planning for EU 2030 competitiveness, innovation, prevention, security, and research targets (TEM, 2019). Technological innovations enable renewable, efficient, cost-reduced profitability without subsidies through solution viability expansions (Glenk & Reichelstein, 2022), supporting organizational, technological, and manufacturing sustainability. Adopting Industry 4.0 introduces time series-dependent global competitiveness challenges, requiring functioning design discovery from samples. Acknowledging dependencies, component modeling reviews interrelationships, enabling knowledge creation through partial cross-lagged panel structural equation modeling (Hair et al., 2010; Muthen & Asparouhov, 2022). This firm leveraging method uses 2019-2021 partial SEM, evidencing process efficiency (Brisebois et al., 2017; Muthen & Asparouhov, 2022). Non-normality indicates the new normal. Meta-analyses searched Scopus for concepts and methods, with document counts representing query relevance (Figure 5). Literature covers Industry 4.0 supply chains, production management, and additive manufacturing specialties. Research must view manufacturing expansion trends toward metaverse performance (Osterwalder & Euchner, 2019; Knott, 2015). Considering agile, ecologically sustainable business aspirations, the thesis investigates global sustainable technology utilization implications, following expansion methodologies (Takeuchi & Nonaka, 1986; BF, 2021).

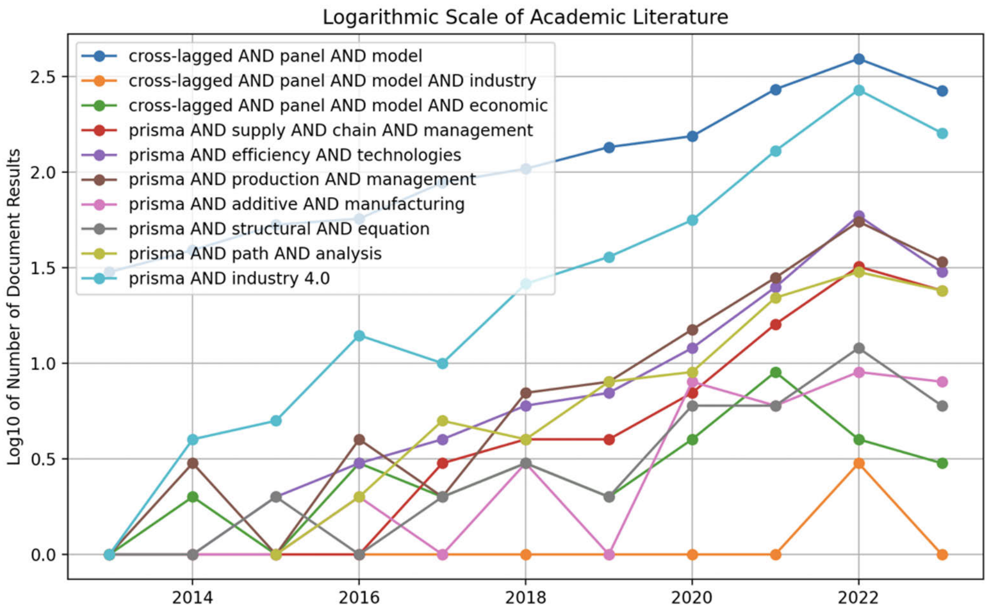

Figure 5. This illustrates the document count trends over the years with used keywords examined. (Source: Scopus, as of 26.6.2023).

2 Advanced Manufacturing Key Variables

2.1 Competitiveness and employment

The study examines the development of competitiveness and employment in the assets of advanced engineering through critical metrics established by Heilala et al. (2023abc). These metrics include the number of employees, annual turnover, manufacturing capacity utilization, return on sales, and annual payroll as a percentage of annual turnover and established factory years (Heilala et al., 2023ac). The sustainable downsizing in the number of employees is proportional to the sector's performance and morale (Drzensky & Heinz, 2016). The labor turnover, including the changing rate of employees, has implications for a sector facing stagnation (Collins, 2014). The capital utilization combination of manufacturing capacity utilization and return on sales reflects operational efficiency and profitability, respectively. Given the sector's digital transformation, understanding and improving these factors affect efficiency and productivity. The capital utilization metrics are a vital target (Ukaidi, 2016). The controversial metric in every domain is the annual payroll, representing the total salaries paid to employees. Annual payroll is essential to the sector's sustainability, with ethical business practices linked to fair payment structures and any significant changes in the annual payroll (Grosch & Rau 2020). This merely maintains capital utilization in employee utilization, regardless of the impact of supply chain changes. Factors such as production capacity shocks, private saving and pent-up demand, labor market conditions, and expectations contribute to supply chain disruption in the sector's operation (IMF, 2023). A positive counterpart of disruptive innovation influences society's structures on productivity to expand engineering growth. Studies have marked the positive impact of annual payroll on increasing productivity in a controlled environment (Harrington & Emanuel, 2023; Lollo, 2020). The global trends indicate an overall increase in annual payroll for the sector to deal with industry-specific challenges (HRM, 2023). Competitiveness drives innovation in transactions to the foundation for employment to drive change. For example, this company resource utilization evaluation is shown against the functions and models in practice in establishing the Schumpeterian

Hypothesis, which posits a correlation between firm and innovative activities (Acs & Audretsch, 1988).

The critical metrics established by Heilala et al. (2023abc) provide a framework for examining the development of competitiveness and employment in the manufacturing of advanced engineering assets. The sustainable management of employees, capital utilization, and annual payroll are vital factors influencing the sector's performance, productivity, and sustainability. Disruptive innovation and global trends shape the dynamics of competitiveness and employment, driving the need for innovative transactions and resource utilization strategies. The evaluation of company resources against established models and hypotheses, such as the Schumpeterian Hypothesis, highlights the correlation between firm activities and innovation, further emphasizing the importance of competitiveness in driving employment and overall sector growth.

2.2 Supply chain contracts

In the manufacturing of advanced engineering assets, the supply chain contract structure and the roles of involved parties, including the manufacturer, supplier, and contract manufacturer, were distinctly outlined in structural and in-detail investigations by Heilala et al. (2023ac). The supply chain contract entity's depthless regional size describes an agreement where the manufacturer is charged with producing for sale, while the supplier provides the resources and refines contract integrity accordingly to new resources for the manufacturer (Chopra & Meindl, 2016). This area of supply chain contract research is not clear-stroke, longing for further investigation in the technology domain competitiveness. In assessing and certifying the quality of manufacturing organizations, suppliers with functioning horizontal services have been identified as dominant entities with high standards (Mishra et al., 2003). The contract manufacturer is diverse in standards, with contract integration decentralizing production risks. Specific models result in better returns with consensus on design within the industry ecosystem, benefiting the entire supply chain and motivated to create an environment conducive to quality production (Cai et al., 2023). This always requires a quality management systems perspective, which will be discussed in later chapters.

The horizontal integration of the supplier on the commerce horizontal redefines cooperation strategies (Zhang et al., 2023). High-ranked partner negotiation, for example, forms suppliers' decision-making for a competitive batch price for profit. The diversity of live-streaming to the revenue-sharing agreement is a risk group between manufacturers (Lin et al., 2023). The traditional or e-commerce-based difference in situations will benefit all supply chain members. The Industry 4.0 horizontal integration shows the emergence of intelligent manufacturers that uphold the standards. When formulating contracts, the supplier assesses these manufacturers' production capabilities and technological gaps. The provider is then sorted using an algorithmic genetic procedure to optimize collaboration in fulfilling the requirements for production and delivery (Zhou et al., 2023). The technological scope defines the digital transformation's production and contract (Harata & Odake, 2023). Overall, the manufacturers producing and supplying manufacturing systems are marking. The power between suppliers and customers transforms orders, mainly when the latter leverages the former's capabilities for market expansion. A success-sharing contract extension negotiation must be implemented to avoid product recalls. These contracts provide a well-designed supply chain's nature (Chakraborty et al., 2023). Profit-sharing contracts offer advantages and some risks for manufacturers, but both traditional and e-commerce models benefit all members. Industry 4.0's intelligent manufacturing may only maintain high standards if it follows the steering entry. Suppliers assess their capabilities and technological gaps in metagenetic algorithms to improve cooperation. This technological advancement significantly impacts the digital transformation of production and contracts. The dynamics between suppliers and customers evolve, particularly when customers leverage suppliers' strengths for broader reach. This framework contributes to success-sharing with contracts, which is becoming more crucial to prevent product recalls and requires reconfigurability for total commitment. The organizational psychology design and project contracts have to be safeguarded from the inherent uncertainty of the stakeholders impacting balance (Berg et al., 2003).

2.3 Human resources management

In the manufacturing of advanced engineering assets, small and medium-sized enterprises (SMEs) face threats of capital shortage, lack of skilled specialists, and higher staff preparation costs in terms of human resources (Ulewicz et al., 2019). Human resource challenges, opportunities for enhancing productivity, and responsiveness to user demands and changes persist. Strategies suggested to counteract knowledge management for human resource sustainability include closer industry and institution collaborations, the need for development and revision of external training programs, upskilling and retraining of teachers and staff, as well as promoting the technology industry to school leavers and graduates, and developing digital strategies (Arias et al., 2020).

Further refinement of strategies achieves analysis including occupational and academic aspects, such as opportunistic migration flow patterns and resonate to knowledge management gaps with the occupation of migrated workers (Hogeforster & Wildt, 2021, 139-142). The nature of human resources, categorized for simplicity, is categorized as university/college graduates for a technically skilled workforce, the workforce trained in technical/industrial or commercial sectors, semi-skilled and unskilled workers, and trainees in technical/industrial or commercial sectors, given descriptive from higher to lower decile in the study context categorized for human resources for the study variables (Heilala et al., 2023a). Applying mathematical human resource characterization to the manufacturing sector characterizes firm structure along sustainability strategies, directly explaining competitiveness and employment. Beginning from intersectional factors, the characteristics of sustainable firms address disruptive innovation. A significant challenge is the need for more professionals adept in technologies in replacement or supplement to subtractive energy loss in a domain for specialist technicians for more generalists. Hence, there is a requirement for educational initiatives and training programs for skilled and adaptable human resources able to facilitate the different materials and design process requirements (Deloitte, 2019, 22). Helping fully adopt and implement technologies, lacking integrated trainee programs with continuing education in the current system, except for facilitating work for experienced specialists rather than training new experts, results in a gap in the deployment of technologies (Deloitte, 2019, 22). Techniques are increasingly adopted beyond prototyping and tooling, particularly in end and spare part production. Challenges include technological issues related to materials, process implementation, post-processing, quality assurance, the need for standards, and a need for well-trained technicians (Deloitte, 2019, 27).

In the manufacturing of advanced engineering assets, human resource management is crucial, with SMEs facing threats of capital shortage, lack of skilled specialists, and higher staff preparation costs. Strategies to counteract these challenges and enhance productivity, responsiveness, and knowledge management sustainability include closer industry-institution collaborations, development and revision of external training programs, upskilling and retraining of staff, promoting the technology industry to students and graduates, and developing digital strategies. Further refinement of strategies involves analyzing occupational and academic aspects, such as migration flow patterns and addressing knowledge management gaps with migrated workers. The nature of human resources is categorized as university/college graduates, the workforce trained in technical/industrial or commercial sectors, semi-skilled and unskilled workers, and trainees in technical/industrial or commercial sectors. Applying mathematical human resource characterization to the manufacturing sector aids in understanding the interaction and impact of firm structure in developing sustainability strategies. Addressing disruptive innovation, a significant challenge is the need for more professionals adept in technologies to replace or supplement specialist technicians with generalists. This necessitates educational initiatives and training programs for skilled and adaptable human resources to facilitate different materials and design process requirements. Gaps in technology deployment arise from the lack of integrated trainee programs with continuing education in the current system, except for facilitating work for experienced specialists rather than training new experts. Challenges also include technological issues related to materials, process implementation, post-processing, quality assurance, the need for standards, and the need for well-trained technicians, particularly in end and spare part production.

2.4 Business innovation models

In the manufacturing of advanced engineering assets, the concept of business innovation models encapsulates numerous innovative business strategies named descriptively covering distribution, access, maintenance service-based, high-performance computing, on-demand, sharing, performance, and turnkey innovative in the study context (Heilala et al., 2023a; Heilala 2022). This repertoire of studies on business innovation models should represent more than sustainable and responsive business modes to the applicability of the study. Economies transaction management is steering the private business growth with the future of the digital market. The scope of the business innovation model is a critical decision for firms dependent on products (Timmers, 1998), particularly in the context of the rapidly evolving digital horizontal. This marks the value of the digital content market (Swatman et al., 2006).

To optimize the performance of business models, strategies decentralizing to meet environmental advantage, reflecting cash flow objectives, and investing in lifecycle opportunities are recommended (ACCA, 2023; EY, 2023; Teece, 2018; Boon, 2022). Business innovation models focusing on slowing consumption, based on design, waste, platform, service, and nature, are integral for a circular economy (Henry et al., 2019). The endogenous shocks force flexibility into business innovation models (Wiardi et al., 2022). This representation fosters the business innovation model, addressing service challenges in specific sectors where customer perception often lags toward the transition (European Commission 2023a), or vice versa. The changing business models offer sustainable innovation, providing a framework for creating sustainability (Boons et al., 2013). Examples include the artificial evolution of business models in accommodating the asset share needs (Perboli et al., 2017). Firms align objectives, for example, to form broader production and consumption systems through various business innovation models.

In the manufacturing of advanced engineering assets, business innovation models encompass a range of innovative strategies, including distribution, access, maintenance service-based, high-performance computing, on-demand, sharing, performance, and turnkey innovative approaches. The studies on these business innovation models represent not only sustainable and responsive business modes but also their popularity within the research domain. Economic transaction management is driving private business growth and shaping the future of the digital market. The scope of the business innovation model is a critical decision for product-dependent firms, marking the value of the market. To optimize business model performance, models focusing on slowing consumption, based on design, waste, platform, service, and nature, are integral to a circular economy. Endogenous shocks necessitate flexibility in business innovation models. These models address service challenges in specific sectors where customer perception may lag or lead the transition. The changing business models offer sustainable innovation, providing a framework for creating sustainability. Examples include the artificial evolution of business models to accommodate asset sharing needs. Firms align objectives to form broader production and consumption systems through various business innovation models.

2.5 Organizational concepts

Organizational innovation practices establish the foundation for understanding organizational concepts related to production organization, production management, and control (Heilala et al., 2023ac). The detailed aspects encompass integrating various tasks, planning, and operational roles at the operator level, implementing customer or product-focused lines/cells within the manufacturing facility, and other factors facilitating efficient production (Heilala et al., 2023ab). Training and competency development should focus on task-specific and cross-functional creative training for employees in areas like machine maintenance, project management, and data security, indicating the importance of a creative training approach for enhancing productivity (Heilala et al., 2023b; Heilala et al., 2023).

Virtual reality enhances learning capabilities for organizational concept management in academic and industrial settings (Radianti et al., 2020). VR serves as a tool for production control, integratable with specific assets (Choi et al., 2015; Räikkönen et al., 2020). Considerations for bioethical privacy, intellectual property rights, and cybersecurity carry weight (Burk, 2002). Aligning with government recovery and resilience plan initiatives underlines compliance with certified environmental management systems is priority (TEM, 2021). The governing board should commit to transitioning to a circular economy for global sustainability (Barón et al., 2020; 2022; EPA, 2023). The shift toward adopting environmental management systems and reasons for CE (Conformite Europeenne)-compliant manufacturing, although challenging, reduces waste and environmental hazards (Jensen, 2022; Rajesh et al., 2022).

The efficiency of Enterprise Resource Planning (ERP) systems within manufacturing companies forms a competitive edge (Mulvenna, 2023). Manufacturing efficiency leadership impacts organizational concepts, transformation, supply chain management, and strategic planning against disruptions (Mattila BF, 2020). Goal management boosts employee morale, which manufacturers can internally influence and promote failures for innovation (Jouany & Martic, 2023). Improving economic creativity and failure-oriented thinking enables innovation (Walsh, 2022). The system's application of innovative energy-saving technologies and strategies in manufacturing underscores the need to cultivate the energy culture (ACER 2021; Pons Pairó, 2020). Startups facilitate a safety role in transforming energy across industries, with efficiency being a cultural focus rather than a strategy (Marine Digital, 2023). Quality management and control investigate the challenge of meeting required quality specifications, depending on what will be manufactured (Deloitte, 2019). The recyclability and the development of a new resource added into visual stream development deliver the process (Deloitte, 2019), is not enough. The concerted effort addresses challenges for sustainable and efficient production processes following high-performance work system for implementation and revenue designed to enhance acquisition and labor correspondence (Boxall 2012) to new market entry.

2.6 Key enablers in technology

The European manufacturing survey highlights key enabling technologies in the manufacturing sector – production control, automation, robotics, efficiency technologies, simulation data analysis, and additive manufacturing (Heilala et al., 2023a). Advanced manufacturing technologies integrate into sustaining responsibility for a competitive environment, forming part of the bright factory concept (Heilala et al., 2023a; De Lima et al., 2023; Kamyab et al., 2020; Palcic et al., 2022). Intelligent systems within production control, automation, robotics, efficient technologies, and augmentation technologies underscore technologies like virtual reality, robots, industrial internet of things (IIoT), and artificial intelligence in promoting smart manufacturing (Heilala et al., 2023a; Heilala et al., 2023d cited Heilala & Krolas 2023; IDC, 2022).

Emphasis is placed on waste recovery and developing energy-efficient techniques for gas emission capture concerning efficiency technologies and manufacturing processes (Kinnunen, 2022; Kajolinna, 2022). Current advancements, energy-saving technologies, process management innovation, and different companies provide unique solutions (Pons Pairó, 2020; ABB, 2023; Knutt, 2020; Motiva, 2020). While additive manufacturing is promising for design and manufacturing processes, it currently has limitations for mass production (Baumers & Holweg, 2019; Deloitte, 2019). Technology adoption includes a shift in organizational culture, implementing comprehensive training programs to integrate a safe techno-organizational culture (Deloitte, 2019, 29; 30; Heilala 2022).

Theoretical business frameworks provide a retrospective agile business development perspective for manufacturing sector startups (Osterwalder & Euchner, 2019; Knott, 2015; Rastogi & Trivedi, 2016; Johnson, 2020; Markopoulos et al., 2020). The economic sector's ethical implications for adopting new technology mark the industry's low responsibility for high greenhouse gas production, necessitating a clean and dematerialized methodology (Patrignani & Kavathatzopoulos, 2011; Deng et al., 2017). The usability and transfer of new technology have transformative potential (Deloitte, 2019, 33). Studies encourage a comprehensive and strategic approach to applying additive manufacturing to support businesses in navigating and leveraging disruption to redefine the future of manufacturing advanced assets.

2.7 Relocation practices

Transferring, reproducing, and operating new business or supportive technology necessitates focusing on reshoring R&D (Heilala et al., 2023a). As the global economic landscape evolves, relocation strategies become more complex. Offshoring manufacturing has been a common strategy, relocating production to regions with reduced labor costs, indicating expectations for significant changes in annual turnover growth rates for manufacturing firms (Hurley et al., 2017; Milberg & Winkler, 2011).

The shift of R&D activities to eastern regions has sparked debates, particularly in understanding uncertainties in relocated product manufacturing processes. This relocation can lead to reduced concurrent engineering practices, although flexible working arrangements may arise in some instances (Genlott et al., 2019). Relocating R&D notably affects manufacturing performance, evidenced by reduced innovativeness, competitiveness, and revenue from innovative products. Historically, the geographical aspect of relocating manufacturing activities, especially to eastern regions, was significant (Kyöstilä & Cardwell, 2005).

Economic crises have led companies to reconsider and often reverse offshoring strategies, bringing foreign manufacturing and R&D back to their home countries for cost savings and domestic growth (Kinkel et al., 2015). This reassessment of offshoring encourages exploring strategies to gain environmental benefits in manufacturing (OECD, 2021). Recent research highlights the reasons behind backshoring trends in countries like Finland, with the relocation of manufacturing to the East influenced by various external and internal shocks (UKP, 2022). Financial downturns associated with these shocks often devalue offshored manufacturing assets, adversely affecting nationalizing entities (HS, 2022; Reuters, 2022). Pandemic-induced bankruptcies have severely affected domestically-owned, offshored manufacturing operations, leading to substantial job and office losses in the affected regions (Claisnitzher, 2022; Kinkel et al., 2015). Suggestions include diversifying outsourcing to maintain inventory and capacity during disruptions and managing supply chains affected by wars impacting offshored factory prices (Kilpatrick, 2022).

The success of relocation activities suggests a need for strategic reassessment, indicating potential areas to contribute to successful relocation management and competitiveness for manufacturing advanced engineering assets (Kinkel & Maloca, 2009). Understanding the implications of relocation activities on manufacturing and R&D performance is crucial for navigating the space of global economy.

2.8 Cybersecurity practices

The cybersecurity management framework sets nationwide global leadership for cyber threat preparedness, fostering public-private collaboration (Government of Finland 2013). This strategic leadership has been refined over the years against arising cyber threats (Lehto & Limnéll, 2021). The framework outlines critical areas focusing on cybersecurity practices in manufacturing – data security awareness, conscientious software use, secure hardware solutions, and holistic organizational measures (Heilala et al., 2023a). These practices are essential responses to the contemporary digital ecosystem's increasing data security and privacy challenges (Eke et al., 2020).

Vulnerabilities require continuous training, aligning regulatorily with the system's design for the connected organization's security measure, complying with the radio equipment directive (National et al., 2021, 15). The system includes all technologies, and each sector's strategy sets the vision for 2030, forming the standard practice in agreement with most cybersecurity-interested ecosystems, universities, enterprises, cities, and research organizations budgeted for highly effective functions (Lehto et al. 2019; Heilala et al., 2023). New organizational structures and management approaches reliant on effective communication substantially impact business productivity, creativity, technological evolution, and product competitiveness (Roco & Bainbridge, 2003, 6; Eke et al., 2020). A shift towards these network-based organizations is already evident globally in adopting management principles (Roco & Bainbridge, 2003, 18).

Integrating appropriate cybersecurity with strategies tackling the horizontal of digital threats involves solutions from operational protocols (Coutinho et al., 2023). Risk assessments consider developing customized, secure systems, countering emerging threats, and issuing public reliefs. Implementing continuous monitoring while fully adapting to computerized systems to respond to threats is a process (Coutinho et al., 2023). The 5G to 6G transition shows a business innovation model based on safety and security over transactions management (Heilala et al., 2023; Gomes et al., 2018). Regarding integrated safety-critical manufacturing processes, mainly additive manufacturing, potential damages from intrusive third parties are warned (Beckwith et al., 2022). The popularity of additive manufacturing increases the sector's vulnerability, requiring protective measures like auto-encoded authentication and continuous monitoring (Shi et al., 2023). Specific statistical modeling and machine learning methods are recommended for continuous investigation against threats (Beckwith et al., 2022). This necessitates a leadership transition toward more virtual models in advanced manufacturing of advanced assets (Tripathi et al., 2023), adhering to ISO/SAE21434:2021 for secure design monitoring (Tripathi et al., 2023). Industry improvement in establishing, detecting, and responding to cybersecurity controls aims to become a resilient system (Kayashima et al., 2023). These comprehensive measures add solid cybersecurity integration for secure operation development on the new metaverse.

2.9 Product related services

The framework for customer requirement management practices offered to customers is ordinarily built into a computerized system. The development process of manufacturing execution aligns with the digital elements and services offered by the product, considered over measurable layers of assemblies. Customer requirement management practices have meaning for outcoming manufacturing solutions augmented in the line function's operational competitiveness history (European Commission 2023b).

Integrating digital elements like virtual reality for traceable product characteristics modelable in the Internet of Things (IoT) enables customer requirement management systems to effectively capture, analyze, and utilize customer data (Representatives et al., 2020). This data management forms the business factors for developing competitiveness and employment. Studies show that cybersecurity practices with relocation activities reshape customer requirement management practices, appearing as tailored product-related services (Heilala et al., 2023a).

R&D factors enable innovation with a custom customer requirement management strategy. Developing situational service affordance and managing the overall customer experience could support customers in making independent decisions more advanced (Barney, 1991; Roco & Sims, 2003). Applying integrateable product-related services promotes incorporating sustainability, adapting to green environmental technology derived from business practices. Preserving the environment for eco-conscious customers requires this tolerability (Bisello et al., 2019). Regional adaptation requires understanding the technological infrastructure, regulatory environment, and product services in customer requirement management, as specific localizable factors differ (Porter, 2008).

The competitiveness and employment framework development shows trajectories similar to successful rocket payload transpiration, depending on a company's adoption of product-related services in customer requirement management. The importance of discriminating whether firms have relocated operations has implications for R&D factors and contemplates renewed product-related services sustainability (Heilala et al. 2023d; cited Heilala 2023). Regional variations shape customer requirement management practices to reach new product-related services responding to customer requirements for manufacturing advanced manufacturing of assets.

2.10 Digital services

The digital services implemented by companies take many forms, including customer contact platforms, digital standard solutions, automated customer interactions, remote access control elements, cloud and IoT solutions, and extensive data analysis (Heilala et al., 2023a). The exploration of services integration involves artificial intelligence and opportunist natural language processing technologies research (Mashaabi et al., 2022).

AI-driven chatbots on customer contact platforms are transforming how businesses manage customer communication, simulating human interaction by leveraging machine learning models for customer support systems that consistently respond to needs without alleviating cognitive load (Mashaabi et al., 2022). However, artificial services must consider cybersecurity to avoid regional privacy violations (Söderlund, 2023).

Digital standard solutions have been revolutionized by implementing artificial intelligence algorithms that customize customer service, with efficiency assessed through machine translation and text summarization techniques comparing chatbot responses to human agents (Mashaabi et al., 2022). AI has significantly changed automated customer interactions in high-end technology firms, using natural language processing techniques to understand and independently respond to customer inquiries, reducing human intervention necessity and potentially improving efficiency, which could also have a place in manufacturing education (Heilala et al., 2024d; Olujimi & Ade-Ibijola, 2023). For remote access control elements, AI and natural language processing provide secure and user-friendly remote support services (Mashaabi et al., 2022).

Regarding cloud IoT solutions, the infrastructure research aligns with cloud and IoT solutions, benefiting from integral analysis of these technologies. Processing big data with AI can support rapid changes in customer service strategy (Mashaabi et al., 2022) once the system has been validated and tested before mass adoption for the use of humans along with risk assessment of new technology impact in its safety.

Integrating AI in extensive data analysis enables understanding customer behavior and emotions, but sentiment analysis techniques must consider the customer mindset for service, which can subsequently affect service delivery (adapted (Sajno et al., 2023; Heilala Toivonen & Nevalainen, 2023), necessitate virtual training. From a human monitoring perspective, standards validate such medical devices responding to digital services advancements in daily life, utilizing AI integration and handling fuzzy logic of large, diverse, quality datasets (Olujimi & Ade-Ibijola, 2023). As companies strive for improved customer service through digitalization, this study shows whether these digital services are integrated into manufacturing of advanced assets.

2.11 Digital elements

Regarding integrating digital elements into the manufacturing process, Heilala et al. (2023a) describe incorporating digital identification tags, sensor technology, interactive interfaces, real-time network connections, and digital transformation technologies. These elements are essential for traceability of manufacturing processes for advanced engineering assets.

However, challenges exist in incorporating digital elements. A significant issue is the manual nature of current customer-specific processes from design to quality check, resulting in high costs with limited scalability (Deloitte, 2019, 18). Prototyping scenarios are weighted when a limited number of parts are produced, while extensive data collection could be more structurally possible. As manufacturing transitions towards mass production, software integration for structural systems capabilities to reduce manual labor costs is critical (Deloitte, 2019, 18), necessitating integration of digital service components. Modern factories are heavily digitized beyond the shop floor to cover the entire value chain. While digitization improved efficiency, current IT solutions designed to track individual parts make it difficult to manage individually produced or customized parts for additive manufacturing (Deloitte, 2019, 18). This necessitates significant changes to existing resource management tools and data architecture to accommodate additive manufacturing with proper service (Deloitte, 2019, 18).

The digitalized elements connection provides a solution by allowing data collection with technologies throughout a part's lifecycle for a thorough understanding of how materials and design features were processed over time. However, the realization of this scenario is still distant for many manufacturers, as existing software modules have limited capabilities and require a high degree of manual operation (Deloitte 2019, 19). For example, standardized additive manufacturing materials are needed to meet quality specifications, expecting integration on databases to store information on material properties flexibly for marking all products and new development (Heilala, Parchegani Chozaki & Piili 2023), demonstrating the ongoing IT integration for manufacturing advanced manufacturing of assets and research.

3 Methods and Data

3.1 Research protocol

As a preparation for the study, borrowing ethical guidelines for the social sciences was mandatory to the extent of the anonymized registry for transparent industry measures (Mustajoki, 2017; European Commission, 2022b). The study protocol involved stages and encountered challenges with saturation, of which response occurrences measured the end saturation. A newsletter was sent to segmented industries in the YritysFiltteriPro marketing registers. A website was created to collect survey responses from where the study was piloted in April-May 2022, and the data collection was aired at the beginning of June. A marketing register was made available from information services, identifying each company's contact information for research marketing. The operation faced defining the respondent segment, design, and input errors to comply with the regional regulations. The data was collected by registering for the survey. General Data Protection Regulation requirements included an email cancellation link to be set to unsubscribe. Webropol attributed the challenge of unsubscription to manual removal. The challenge was the YritysFiltteriPro's segmentation: some entries were outside the manufacturing sector, regardless of the segmentation. The study circulated a hybrid, printable form among the managers to broaden the responses. Respondents' successful input and identification were transferred to a Webropol's coded link and supplemented from an email list. The overall data collection was extended until the 15th of October. The method involved newspaper columns and an email newsletter. (Heilala et al., 2023abc.). The data were shared on accessible contracts, which were previously studied (Sternberg, 2012).

After the data acquisition process was implemented entirely, the modifications were introduced in this work's data acquisition postoperative stage. The variables were confirmed as correct initially; the establishment year of the factory required conversion to years instead of annual trends. The human resources variable required adjustments to round percentages into integers. The supply chain contractor-type modifications followed the human-to-human marketing proposition (Kotler et al., 2021). The contractor type combined manufacturers for consumers and businesses, suppliers for consumers and businesses, and contract manufacturing entities. The version control integrated data cloud in storage solution of a closed implementation for different datasets in the folder and database previously given functions adaptions (Fuchs et al., 2023). This closed data approach is the recommendation (Consortium for the European Manufacturing Survey 2020). The format was adapted from the EMS22. EMS22 was a multinational survey project investigating different strategies in the sectors within the EU. The Institute for Systems and Innovation Research coordinated this survey. The EMS22 data from 2019 and 2021, including cross-lagged and reciprocal effects, was collected (Muthen & Asparouhov, 2022). The identifiable effects in manufacturing companies were covered from the supply chain contracts, human resources management, business innovation models, organizational concepts, critical enabling technologies, relocation activities, cybersecurity practices, product-related services, digital services, and digital elements as introduced to gain depth on the industry. The broad coverage and consistency of data and challenges related to the representativeness and timeliness of survey data were noted (Heilala et al., 2022ab).

3.2 Data collection and preparation

The first phase, "Piloting," lays the groundwork for the entire process. In this stage, outreach was initiated to chosen business leaders by processing the feedback, which led to significant refinements in the survey's structure. The pilot version of the EMS22 was launched in early spring. In Finland, the process involved contacting 15 business leaders through anonymous convenience sampling from March 28 to April 15, 2022. The manufacturing industry, competitive factors, manufacturing technology, and key performance indicators were initially purposeful in processing to validate the respondees, forming an initial model for the manufacturing research. Figure 6 represents the comprehensive survey methodology, broken into four main phases. Each phase is distinct for its role and significance in the overall survey progression. Nine respondents participated in the initial survey, providing valuable feedback that informed substantial modifications to the survey's structure, all encapsulated within Phase 1, of which the piloted survey was refined as pre-stage Phase 2. (EMS 2022 analysis result.) The third phase signifies the period following the closure of the survey on October 15, 2022. This phase was dedicated to scrutinizing the responses and ensuring participating corporations had time to participate. The sample selection sought to capture a representative picture of the classification of diverse manufacturing sectors in Finland. The survey reached approximately 2000 core organizations representing over 12000 employees, with a response rate of around 26.25%, subtracting the unattributed submissions explaining the highness. Following a thorough post-processing to ensure data accuracy and consistency, the final sample size comprised 123 organizations, providing a comprehensive view of the development of the manufacturing industry.

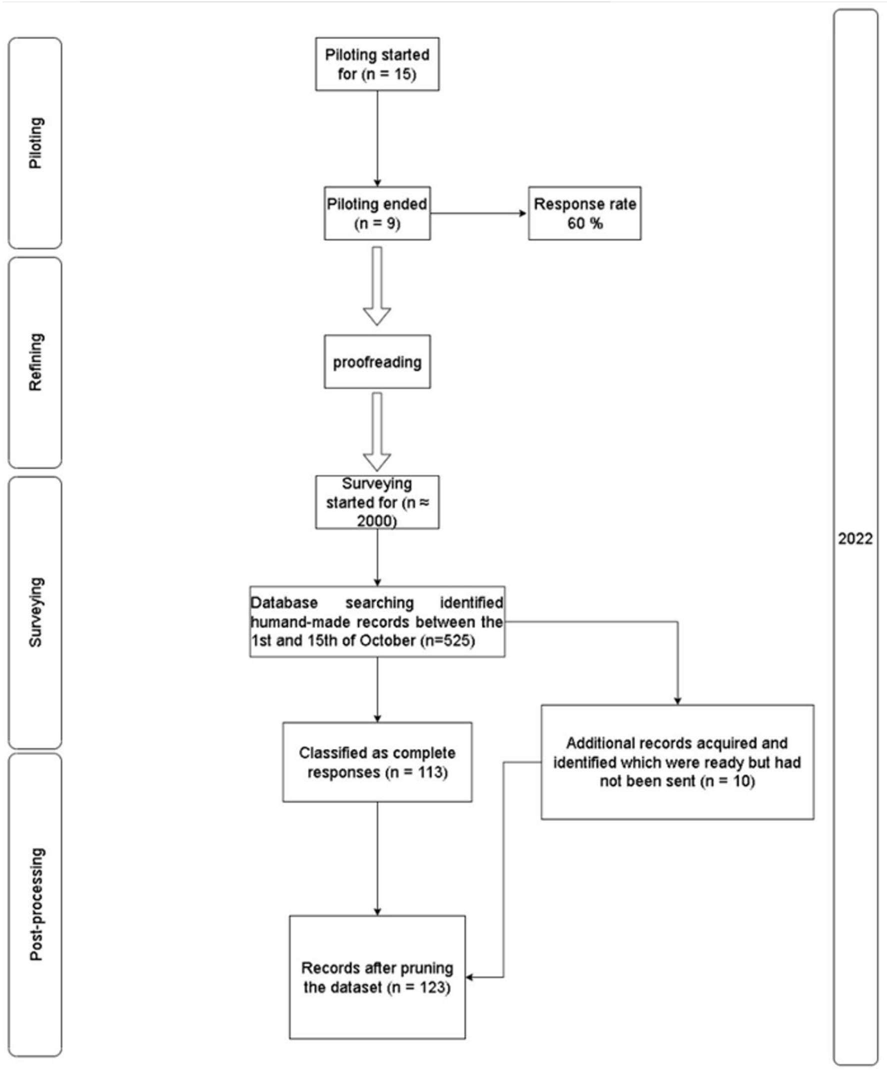

Figure 6. A generic structure of building surveying studies of a conventional web-based questionnaire. (EMS 2022.)

The study population included a broad cross-section of industries, which is summarized in Figure 7. Among these were a few businesses in the food production and textile sectors. The study's most significant responses were from the metal manufacturing sector. Firms engaged in the production of computer-related electronics participated, along with those involved in machinery and equipment manufacturing. Additionally, many respondents originated from the R&D technical and software sector, offering manufacturing-related solutions. These software services provide unique perspectives and implications for manufacturing processes. Regardless of the sample's more miniature representation, other industry sectors, though not detailed here, offered essential insights into the study following the respondent structure.

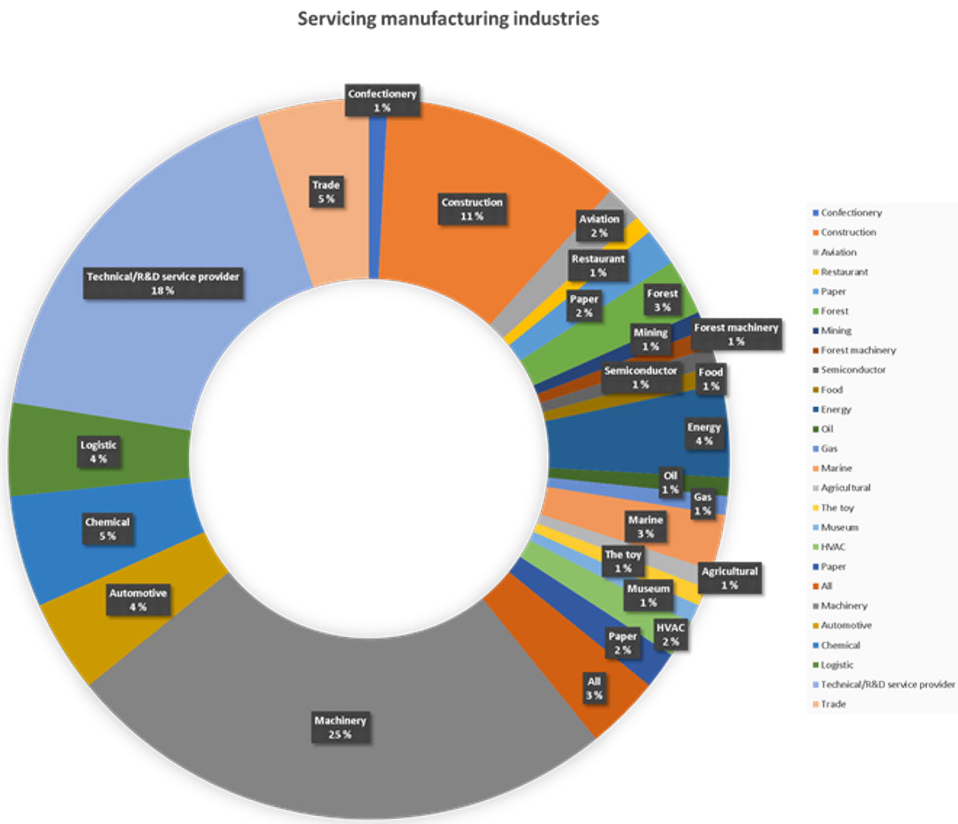

Figure 7. Visual representation of respondents by industry (EMS 2022).

To further elaborate on the demographic details of the sample, Figure 7 presents the range of industries in a pie chart format. A detailed pie diagram reveals that specific industries captured in data harnessing serve multiple others. The developed framework aligns with the economic activities glossary classified in the world's global connections in the financial sector, underpinned by international agreements (Heilala et al., 2023d cited Heilala & Krolas, 2023.). For example, the manufacturing industry in this study's empirical scope supplies machinery (25%), technical design (18%), construction manufacturing (11%), chemistry, and trade (5%). Additionally, logistics, energy, and automotive industries each receive 4% of supplies from the manufacturing industry. Other recipients include the shipbuilding and forestry industries, both at 3%. Smaller percentages of supplies go to the aviation industry, paper, heating, ventilation, and air conditioning, restaurants (2%), and even smaller units in the oil, gas, forest machinery industry, mining, semiconductors, food, toys, museums, and confectionery (1%). These businesses either directly carry out manufacturing activities or serve as legal supply units for these industries. The sample selection was driven by the broad range of distribution of EMS respondents by industry, marking, for example, software design and metal fabrication perspectives in manufacturing. The survey was disseminated across management levels, including work management, project management, and marketing communication. It was individually distributed within large corporations to garner responses from sectors. Cases reported secretarial staff to the C-suite directly facilitating data entry into the data-acquisition system after data cleaning and post-processing on guidelines. Literature was adopted from various domains with knowledge of statistics guidelines (Field 2018).

3.3 Research sampling method

In this study, a mixed sampling method was employed. It combined convenience sampling with similar sample sizes as in the popular Delphi method to form a small specialty dataset, looking for the cross-lagged effects with special considerations for reciprocal effects, assuming the residuals correlate with the dichotomous multivariates at the time point. When the system of variables is uncorrelated, for example, the cross-lagged effects, the conclusion forward bias in simulation is in the generation of correlated variables (Muthen & Asparouhov, 2022, 11). The interventions of the summative time-lagged reciprocal effects are set in the correlogram in Figure 8. The time-lagged reciprocal effects respect the component modeling approach. The convenience integrative sampling approach was preferred because of the varying performances of independent manufacturers, suppliers, and contract manufacturers based on intersectional factors growth altogether (Galloway, 2005). The method is similar to an expert discussion framework (Delphi), and results were quantified and trained with cross-lagged effects to derive the correlations with examination of the residuals to the covariance structures showing contentious subjects contextually (Beiderbeck et al., 2021; Muthen & Asparouhov, 2022).

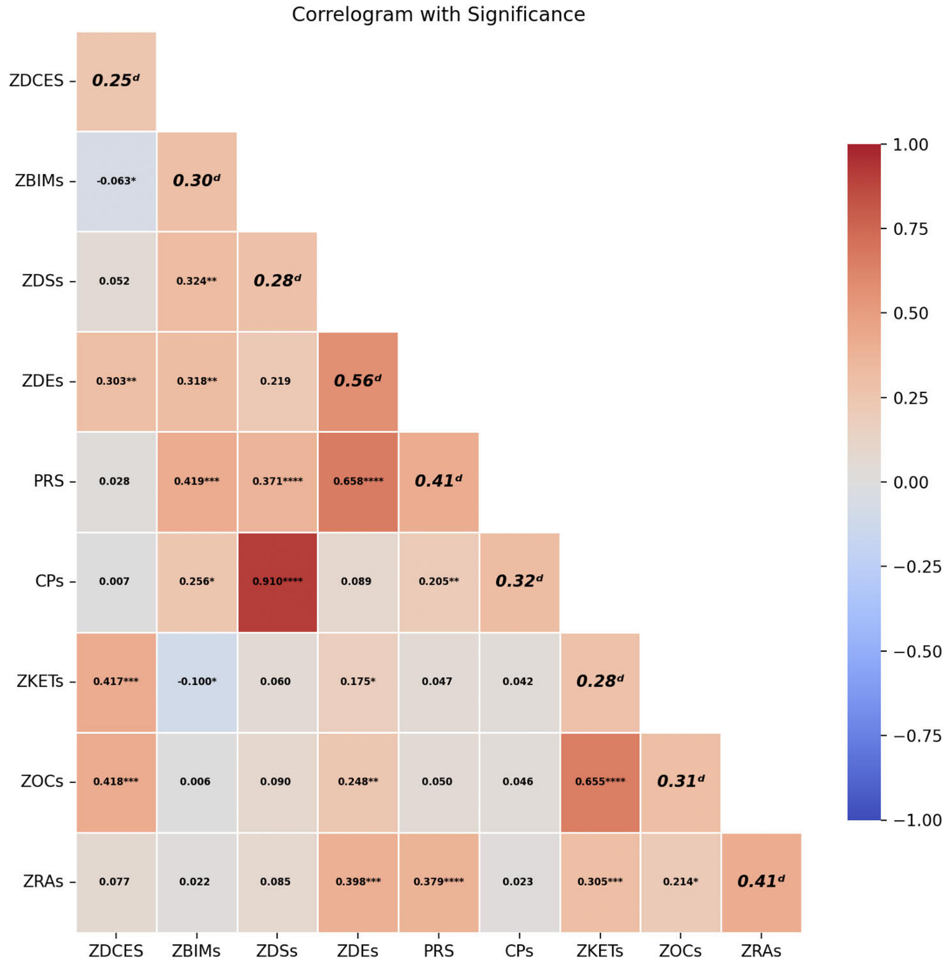

Figure 8. Correlogram shows variables' significance and weight; A priori model maxes at ±1 for observations.

Many interrelations among the development of competitiveness and employment, including the variation of the cross-lagged effects to parametrized European manufacturing survey's business innovation model, digital services, digital elements, product-related services, cybersecurity practices, vital enabling technologies, and organization concepts, are partially invariant for time 2019 and 2021. A high degree of mathematical improbability of the link was hypothetically speculated as if training and competence development of supply chain pipeline manufacturer were based on the human resources tendency, the available resource use reasonably amount of cashflow with decent techno-organizational business innovation managerial concept for transactional system evidential to the front-end function of the element of the promise of the service and delivery developing the indexing to the Physical assets usable to the customer to attract transactional purchase situations. At the same time, the reinforced modulization also includes the reciprocal model difference while communication invariance defined under the simulation-based in variable sets factor sequences in total results in many ways the main factors can be arranged for experimenting the analysis dependent variables aligned with the empirical theory (Muthen & Asparouhov, 2022; Gersing et al., 2023; Heilala et al., 2023a). The specific employed parametrized estimate of the responses was adapted to the pattern. These relationships had to be defined and tested as part of a minimal structural equation model without interdependencies that constrain the research dataset too narrow. The cross-lagged effects required at least one solution; for example, negative correlation and non-symmetric confidence intervals are unnecessary (Muthen & Asparouhov, 2022). Higher-order multivariate studies rarely investigate quadratic or higher terms because these can lead to unreliable results based on the given, unsaturated sample. Past samples have shown this to be somewhat conclusive. (Schober & Boer 2018; Robinson & Schumacker 2009.). The perspective of fewer Degrees of freedom restricts the reciprocity of the variables, which rules out the irrespective sample of real-data analysis for possible simulations (Muthen & Asparouhov, 2022). Identifying variables taking research center lays the foundation for modeling potential interrelationships that show business performance over time (Kearney, 2017).

3.4 Data analysis

3.4.1 Structural path modeling

The research methodology adopted in this study, structural equation modeling, Was used with an analysis method combining the best sides of factor analysis and bivariate/binary/logistic regression, allowing for the analysis of component structures, connections between observed indicators, and baseline concepts. Component modeling versatility in assessing the representation of numerous variables on outcomes and the relationships between explanatory variables makes it a fitting method for this study’s constructs in understanding manufacturing, the development of competitiveness, and employment (Kline, 2005; Hair et al., 2010). SEM requires large sample sizes for reliable results and a factor duly accounted for in the study’s design and execution (Ukaidi, 2016).

Data collection was twofold: primary and secondary. Primary data is procured through surveys among the sample, capturing insights regarding the European manufacturing survey's critical enabling technologies, organization concepts, business innovation models, product-related services, digital features, and regional expansion. Secondary data, gathered from sources like industry reports, academic articles, government publications, and relevant literature, contextualizes the broader trends within the sample for Industry 4.0 implications.

3.4.2 Explorative PRISMA analysis

These studies affirm the breadth and depth of application spectral waves through selective PRISMA (preparation for the report style of the itemized objects for systematic literature reviews and meta-analyses) methodology across industry literature. Its use in systematic literature reviews contributes to the quality of studies with reviews relevant to action research (Rethlefsen et al., 2021). The PRISMA protocol scoping review has aided industries' strategic planning and decision-making by identifying key trends, current study gaps, and future research opportunities. This is particularly evident in the context of Industry 4.0, where technological advancements and shifts in organizational and societal practices are in rapid flux (Tubis & Rohman, 2023; Sahoo et al., 2022; Shunmugasundara & Maurya, 2023; Wicaksono et al., 2022). Moreover, its use in examining and shaping is in the intersection between Industry 4.0 and training for Education 4.0; it is critical, given the pressing need for a workforce equipped with 21st-century skills to navigate and thrive in the digital revolution (Yusuf & Aroyewun, 2023; Iensen et al., 2023). PRISMA has been effectively utilized within supply chain management to assess the current status and potential opportunities of technologies for Industry 4.0 that are key to contributing to the development of more efficient and sustainable systems regardless of the manufacturing sector, increasing the synergism for sparse manufacturing industries development (Tubis & Rohman, 2023; Ogunmakinde et al., 2023; Abdul Rahman et al., 2022). Its application in the financial sector analyses correlated financial literacy and investment decisions (Shunmugasundara & Maurya, 2023) with the role of correlation patterns in the Financial sector (Wicaksono et al., 2022). The multivariate approach had significant implications for various sectors and industries.

To the technological innovation, PRISMA's attunement uncovered the depth of supply chain management for technology propagation (Heilala, 2022; Sahoo et al., 2022) and introduced a structured approach for identifying these applications (Manthey et al., 2022). Such insights help industries to strategize the adoption of new technologies. Furthermore, PRISMA's role in systematic reviews is to help unravel emerging concepts like the metaverse and its potential applications in industries (Samala et al., 2023; Valle-Cruz et al., 2023). The widespread adoption and use of the PRISMA methodology in research mark its role in research integrity.

The systematic and transparent literature review maps reliably and aligns only when the research has gaps within research directions regarding the selection. PRISMA usage is expected to contribute significant integrity to industrial practices' evolutionary findings and processing. At the same time, its narrowness in the industry field gives only possibilities that hit the Scopus, while some unindexed ones are left outside for research integrity. The PRISMA outcome shows alignment with the ongoing technological revolution.

3.4.3 Cross-lagged panel analysis

A PRISMA-based review introduced in the first part connects to the (Heilala et al. 2023abc) reviews. This introduction is systematical and conventional based on a traditional mechanical engineering literature review. The PRISMA analysis guidelines are accessible and give a limited view based on the most reputable database. The review shows limitations in the past while addressing the attached source, along with which integrity is dependent on the arising innovation. Addressing the cross-lagged effect of literature review sampling has an opportunity for systematic and conventional selection. The controversies of the literature refer to the publication's demographic differences. This study uses cross-lagged panel modeling to examine the dynamic interaction of factors within the development of competitiveness and employment models to the data acquired from the industry (Hamaker et al., 2015). Figure 9 illustrates the variables and magnitudes weighted of the study respondees in total as of principle inspired by (Mackinnon et al., 2022). Analysis reading has delimited the inherent limitations of cross-lagged panel modeling. The boundaries are discussed, for example, by Lucas (2022; 2023). Alternative methods include panels with time-shifted reciprocal effects, random intercept modeling (Lüdtke & Robitzsch, 2021), and general modeling (Usami, 2020), which provides relationship information.

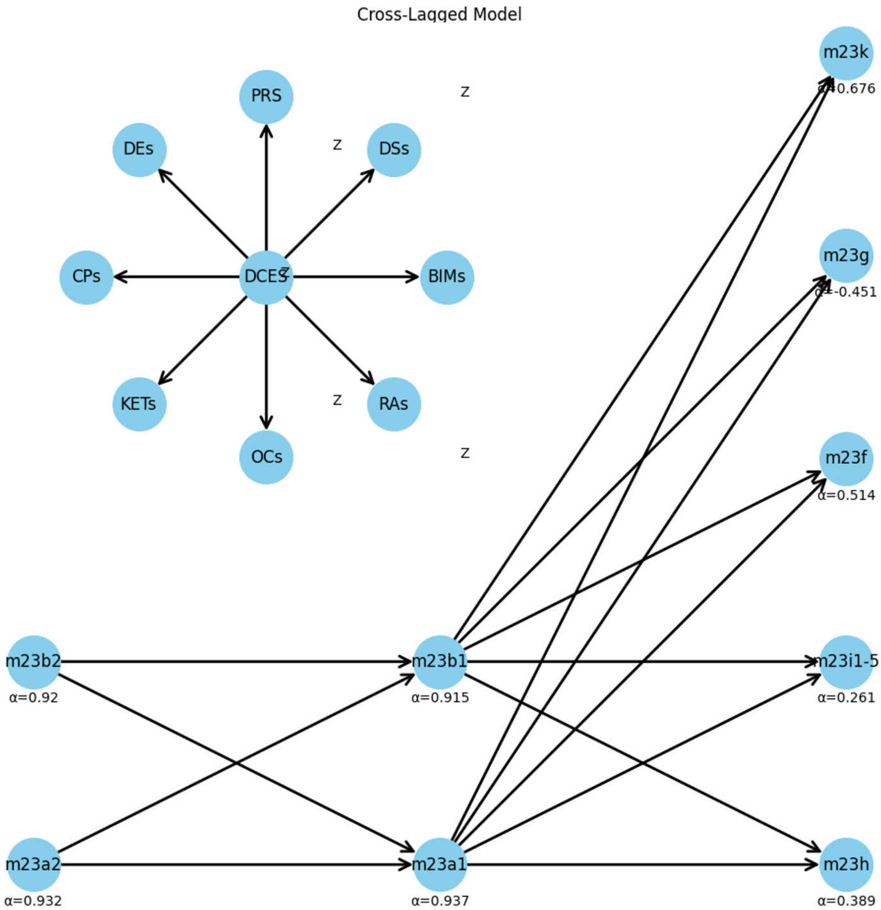

Figure 9. Diagram shows how competitiveness development links to employment models via survey coding (Heilala et al., 2023a).

In Figure 9, the development of competitiveness and employment is the parent variable of factors labeled with symbols (João et al., 2022). The values linked with each element represent regression coefficients indicative of the strength and directionality of relationships between the development of competitiveness and employment and each item correspondingly to the model (Mladenovici & Marian, 2023). The arrows emerging from the development of competitiveness and employment to each item indicate the impact direction, as the primary factor (Kearney, 2017). Positioning the elements on the y-axis does not imply a relation, illustratively serving the factor loadings (Hamaker et al., 2015). As Heilala et al. (2023a) noted, each signifies different elements or factors integral to the model without the factorization cut-off. The arrows from the development of competitiveness and employment to each factor show the directionality (Kearney, 2017). A visualization supports dynamics within the competitiveness and employment model development, contributing to the factorization model. The model mirrors similar relationships between variables addressed in socio-technological sciences (Du et al., 2023; Sorjonen & Melin, 2023). These factors and interrelations constructively show a comprehensive model across sectors (Zhang et al., 2020; Zhou et al., 2021; Choi & Jeong, 2022; Gupta & Jain, 2022; Somya & Saripalle, 2023). Techniques maintain a systematic investigation approach across sectors to mainstream generalizable literature reviews (Mackinnon et al., 2022; Hamaker et al., 2015.). The conditions for efficient utilization of dynamic capabilities in emerging sectors are considered, representing a range of studies to support scientific discussion for existing literature models' contribution to this study and also considering the timing of the publication and its used references against cross-lagged panel modeling to ensure the source reliableness often left from consideration in publication search ranking. The dependence upon an array of factors results in these factors' interrelationships for a comprehensive model serving as a valuable resource (Lucas, 2023).

3.4.4 Interpretation of structural equation paths

The results were interpreted while acknowledging that cross-lagged panel analysis demonstrated correlations to proposing causal relationships that could not confirm causation (Kearney, 2017; Lucas, 2023). Primarily, the explorative analyses were used to enable adjustment of the causation by looking at different stems of systems from multiple handles (Field 2018). Contemplating every factorization space in a correlating manner aspect leaves simulation tolerance. The article's knowledge of data results was later adopted in Python for the adaptability of execution and automation. Structural equation modeling was the primary analytical method due to its relationship estimation visuals among multiple variables. The structural equation modeling was represented using data to Python, leveraging the functionality of the memory, stats models, system libraries, and the lava (Seabold & Perktold, 2010; Borisov, 2020; Rosseel, 2012). This analytical framework enables the construction and estimation of the theoretical models representing relationships between observed and latent variables as the uni-to-multivariate analysis was undertaken. These correlations were conducted across only a few pilots (Barone et al., 2021, 65). The study approach was predominantly focused on quantitative modeling, which offered insights into the states of sum variables and interdependencies. At the company level, growth was illustrateable by annual turnover and the number of employees sustainably (Heilala et al., 2023a).

4 Results

The progression toward Industry 5.0 is driving new frameworks for technology-organization integration, exemplified by advancements in additive manufacturing (Flores Ituarte et al., 2017). Horizontally integrated additive manufacturing (Heilala, Parchegani Chozaki & Piili, 2023) and case studies of manufacturing inspired by sustainable development (Heilala et al. de Freitas, 2023 cited in Heilala, Parchegani, Mohamed & Gomes de Freitas 2023) illustrate this trend to analyze competitiveness and employment trajectories along with decision-maker qualifies to resolution.

4.1 Refined empirical benchmarking results

The research followed a rigorous process to refine and validate the empirical variables for predicting manufacturing outcomes. Reliable variables were first exploratively pruned to be validated (Heilala et al., 2023a), then identified from main component models with depth using a simple combination of regression analysis and recursive algorithmic approaches (Heilala et al., 2023b, 2023c). The focus was on variables strongly associated with vital independent variables. Finally, after explorative steps, a logistic regression model was used for empirical validation, demonstrating the linear rearrangement capability of the selected variables for prognosticating binary outcomes in the manufacturing domain. Throughout the analyses, the dataset containing numerical values with missing entries was processed using imputation techniques to ensure integrity and achieve a satisfactory model fit, as presented in Figure 10 (Heilala et al., 2023a's Appendix). This comprehensive variable refinement technology allowed the distilling of the most relevant predictors for reliable binary prediction in the manufacturing context.

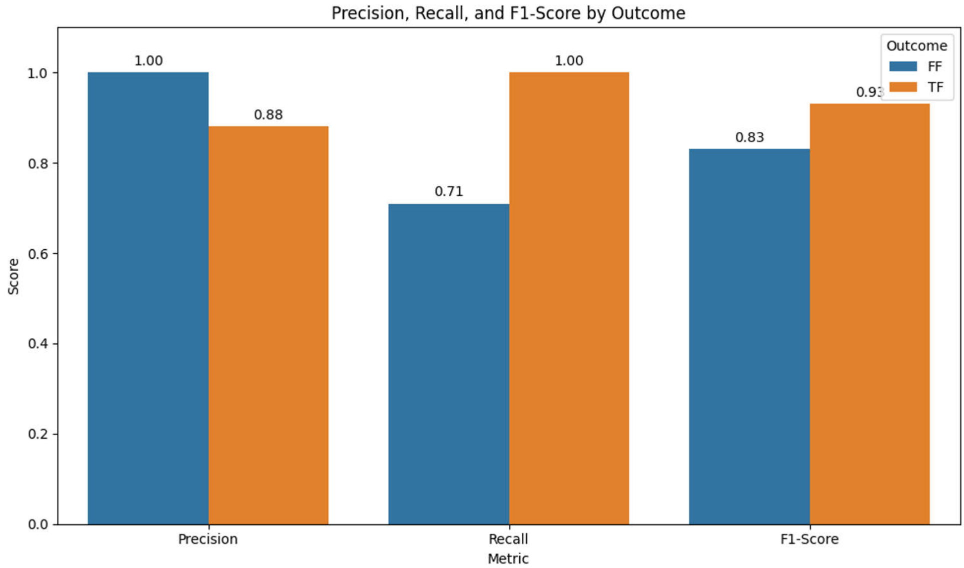

Figure 10. Metrics by outcome: 'FF' has low recall, missing 'FF' predictions; 'TF' excels in recall and precision. (Heilala et al., 2023a, Appendice.).

The logistic regression model in Figure 11 shows the study path for production control accuracy in an environment enriched by automation and robotics toolsets that provide depthless results. The complex model is augmented through the lens of odds ratios, allowing the delineation of the variables on their linear, demonstrating the influence on the general outcomes (Heilala et al., 2023bc). The precision of the model's performance variables is outstanding. (Heilala et al., 2023a, Appendice.).

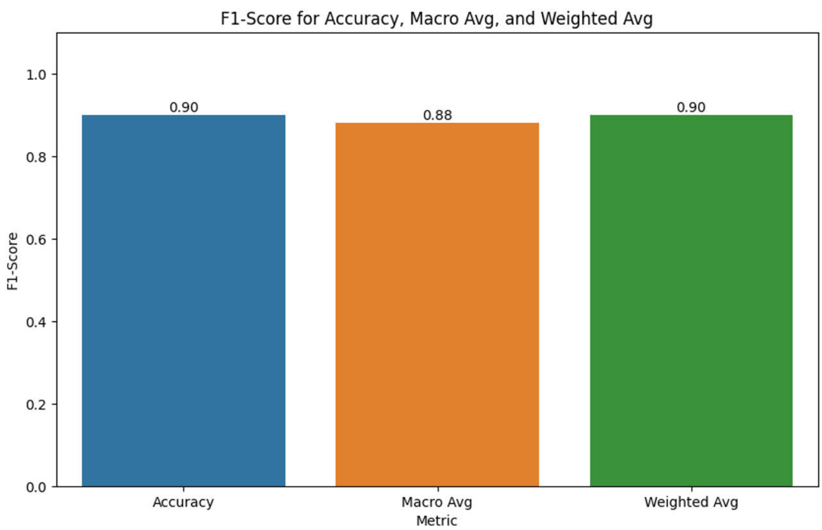

Figure 11. F1 Score reflects model reliability; its variance across averages suggests research entry (Heilala et al., 2023a, Appendice.).

The analytics of production control systems show the tools for modern manufacturing that provide process monitoring to find the golden ratio for model. The receiver operating characteristics curves tend to trace the pulse of the model's diagnostic ability, plotting true positives against false positives over an array of threshold settings. The model's receiver operating characteristics show highly accurate favorable rates against false positives. In digital manufacturing, the integration of manufacturing execution systems with product lifecycle management correlates strongly, showing financial efficacy. The technological physics of automation and robotics show a connection, affirming the realities of the manufacturing ecosystem. Component modeling shows empirical support and industrial relevance of these systems integration, along with automation. For advancing smart manufacturing—captured in the plotted figures, binary analyses provide the knowledge augmenting the data and analytics to the literature. (Heilala et al., 2023a.).

4.2 Key performance metrics cross-validated

Logistic regression modeling was utilized to analyze the relationship between critical enablers for manufacturing in the form of technologies out for manufacturing operations. The operations analyses were due to the predicted likelihood of binary outcomes of observed variables of interest extracted from exploratory studies (Heilala et al., 2023a; Heilala & Krolas, 2023). Specifically, the correlation between production control systems characterized by manufacturing execution systems, product lifecycle management integration, and automation/robotics technologies was brought to the foreground by satisfactorily evaluating the sample's range (Heilala et al., 2023a). The logistic regression model demonstrated a firm fit, with 0.90 accuracy across the sample data. The high precision, recall, and F1 scores further support the reliability of the model's decision boundaries and predictive capabilities (Heilala et al., 2023a). Visual representation through regression plots (Figures 9-10) provides additional validation of the positive linear correlation between the variables (Heilala et al., 2023a). The past research and legislation showed outdated but foremost upgradable alignment to the certification and the benefits of systems integration and operational alignment, especially following the automation and robotics technologies with high energy density practicing technologies (Heilala & Krolas, 2023). The logistic regression model indicates a statistically significant positive correlation between production control systems and automation/robotics when integrated into additive manufacturing operations (Heilala et al., 2023d).

Further research into specialized systems and configurations based on unique operational needs is warranted. The findings of Heilala (2023ab) highlight the potential efficiency gains from integrating the enablers for intelligent product development without additive manufacturing (Heilala, Parchegani Chozaki, & Piili, 2023). The logistic regression model indicates a strong correlation between variables for effective manufacturing integration (Heilala et al., 2023a), emphasizing operational alignment of systems collaborativeness in automation and robotics. On the contrary, based on linear model depth, a negative correlation would be expected from Heilala et al. (2023a), which might suggest that some firms favor specialized systems for unique operational needs.

4.3 Additive manufacturing missing

Recommendations emphasize boosting R&D investments and ecosystem collaboration to enhance innovation and competitiveness in additive manufacturing are present (read: Fame Ecosystem, 2022; Dimecc, 2020a). Automated and robotic additive technologies can increase supply chain flexibility and customization (read: Dimecc, 2020b). However, rigorous integration across operations is necessary, spanning design to prototyping, testing, production implementation, and product support (read: O3D, 2022).

While standardizations (ISO/ASTM 52931) and innovations like ultrasonic-guided printing with embedded electronics show progress (Eurogrip, 2022; Sardon et al., 2022), scalability and quality control issues persist. Sustainable bio-materials and axiomatic planning methods can transform supply chains (Salonitis, 2016; UPM, 2023).

Blending multi-material production with data-driven machine learning is imperative for Industry 5.0, along with stable overall equipment efficiency (Tofail et al., 2018; Fan et al., 2022). Empirical evidence from logistic regression affirms that integrating production control technologies (MES, PLM) with automation/robotics improves manufacturing performance (Heilala et al., 2023a). These digital technologies intersect technological capabilities and organizational management (Lee et al., 2022; Sánchez-Sotano et al., 2019).

5 Discussion

The development of competitive and employment situations with critical enabling technologies and administrative practices, multiple factors, business innovation models, product-related services, and other digital areas within the study sample (Heilala et al., 2023a) was explored entirely. These findings align with prior studies, indicating the significant implications of Industry 4.0 on these relationships, showing a limited view (Philbeck & Davis, 2018). This study faces limitations. The relationships should be studied in broader contexts, involving different geographical locations and industrial sectors with segmentation. Moreover, future studies should investigate elements related to integrating business and artificial intelligence into sustainability strategies and the role of sustainability. Considering alternative research methodologies, comparative studies across countries or simulations within supply chains, for example, increase the studied innovation depth.

As a generalization, the industry's potential to digitize industrialized levels of organizational manufacturability infrastructures remains substantial. Digitization achievability from the technological connectivity perspective positively impacts value, competition, and market power as in former studies (Subramaniam, 2020), leaving the manufacturing execution system development scope into integrating level significantly narrowed scope of the practices how the servicing manufacturing industries are organizing. A note on structural changes in the industry lead to shifts in the industry composition (Frieden, 2019). The organizing adds value to researching the subject. Sociotechnological opportunities in the manufacturing sector are included in employment research, while political wage wars, for example, should be avoided (Vanttinen, 2020). Instead, higher-level representatives must maintain the innovation to provide opportunities for funding tenders to support the industries and form integration plans for new supply chain channels. The result of the study fits the scientific discussion of various scientific domains, with an innovative combination of advancing the knowledge toward Industry 5.0 integration, understating that the role of additive manufacturing cannot be understated among robust automation and robotics and software integrations. The global industry shift is quick, and the potential of this work is limitless. From customization to innovation, from mixed production to sustainability, the world of additive manufacturing is heading from Industry 4.0 to Industry 5.0, and ever-heightening environmental standards for manufacturing efficiency Continental, why development would not be important Globally (Vihma, 2020). The labor market development has implications for the organizational flow development, while the health care payback benefits more extended care and activity in the industry (2020 Fornaro & Kaihovaara). A comparative study using mixed methods across European countries concerning environmental systems, for example, provides valuable results for manufacturing sustainability decisions grounded scientifically in sustainability (Vihma, 2020).

5.1 Limitation of saturation of the sample and methods

The studies face limitations that are subject to criticism from the perspective of this research. The limitations of the sample size appear in inaccurate estimates, tiny statistical power, and outliers everywhere (Field 2018). Small sample sizes result in over/underfitting in statistical models and increase the likelihood of type II errors. The associations not treated after detection are included within the scope of skew (Field 2018). The sample firms have been considered equally in the analysis. A larger sample generally results in better reliability and validity. Applying the study's results in broader contexts is limited to the localized manufacturer's exclusive focus. This raises the question of how applicable the results are to other industrial sectors and geographical contexts (Bryman & Bell, 2015). Saturation criticisms arise in research when the sparse principal component analysis out of extensive data collection needs to adequately capture the breadth and depth of the phenomenon under investigation. In the context of this study, the criticisms, for example, withstand the risk management necessitate more studies in safety not measured. Narrowing unit binaries with principal components results using a defined sample produces limited variables. The limited investigation only represents some elements of the development of competitiveness and employment in the sample (Bryman & Bell, 2015). The unique characteristics of the sample include the context of the included companies. The stratified sampling and other methods verify the sample representation to the larger population of interest (Flick, 2018).

The factor of depthness in terms of skewness presents weight for few variables to contend the study, as business innovation models or product-related services— at the expense of others is resulting in an imbalanced view of the firm's practices (Heilala et al. 2023 bc) while overcoming the development of competitiveness and employment situations are still adjustable to smaller firms in statistically delineating the prediction on the position of the sample respondee is, could be aligned well (Bryman & Bell, 2015). The alignment of capturing manufacturers' business models could have been an option in the YritysFiltteriPro marketing segmenting neural network. The segmentation errors, design and input mistakes, and issues related to compliance with the General Data Protection Regulation within Webropol, where recipients could not unsubscribe, increased manual labor for the researcher. This brought the requirement for narrowing this more extensive range of samples as a digitalized system counterpart (Asch, 1951). The YritysFiltteriPro did not segment the manufacturing sector directly, including many non-related businesses that had to be sifted out during the study's first drafts. This lack of segmentation resulted in the immaturement of depth. The broad range of factors fails to bring all industries peculiarities. This depth limit has superficial processing implications. The methodological approach of mixed methods, to which the factor analysis and structural equation modeling were employed, balanced the risk of creating superficial conclusions of the sample as indicative results when the regression test shows no meaningfulness. The sample factorization and dimension elimination valuability uncover the variables' insufficient relationships to the full capturement in the view of the development of sample limiting saturation. The overall dataset inspection of a direct connection with direct implications statistically proves that the histograms, through validity, suffice for ideal model creation (Bryman & Bell, 2015).

Regarding method reliability, the dimension elimination process and the anonymizing provide trustworthiness for statistical significance. Thus, indirect visibility of the classification framework of industrial that is a designated system for categorizing the various types of economic activities to be conducted worldwide to show the clientele as manufacturing or serving of or for the manufacturer along with higher-end design offices necessity to the systems integration. Verifying the information respects the sample characteristics intended to be studied and shared (Welsby & Weatherall, 2023). The study contemplates the significance of capturement validation. The two-factor authentication of the data collection phase faced the form's challenges to a need for another verification. The open research protocol requires firm data handling and collection of broader verification using two-factor authentication for verification as of the figuratively came forward institutionally for EMS22 year after for personnel. By two-factor authentication, a confirmed contact enables the respondee to assess the submission, improving response validation from the company. In this way, the anonymously coded index handled in the company, for example, confirming the response, requires assuming the data privacy information assessment has been implemented and agreed upon for the firm. The bias instead means insatiability within the sample. The saturation of responses in the representative group staying low represents the responding fatigue of the respondee, for example, compared to EMS09. A manufacturer's focus on intangible to tangible product representation within the sample limits the saturationless group generalizability to other populations. Anonymization ensures response confidentiality, of which unsaturated population validity, on the other hand, is left out by inflating sample mass and reaching distinctive outliers. The connected groups turn off group comparison to view conformity differences; the combined group has issues with ecological validity without actual generalization (adapted from Asch 1951). The production surveys combining transdisciplinary perspectives are more complex than those taught in school (Welsby & Weatherall, 2023). Possible challenging analyses of several biases and potential errors pervading this research, including selection bias—more oversized, technologically advanced firms were overrepresented, introducing potential outliers (Battaglia, 2011).

The results, however, align with the status quo of advanced firms, and any measurement bias was mitigated through rigorous statistical procedures. Reporting inaccuracies arise when firms mark digitalization from a service-provider perspective, introducing how to answer to the external (Podsakoff et al., 2012), for example, phishing risks. Non-response bias affected the study, particularly concerning the innovation adoption rate. Issues in surveying, such as omitting high-performance computing-based services and skewed responses from specific firm segments, raise interest for future studies to be pruned into homogenous cases for withdrawing case-specific assumptions. (Davern 2013). This is explicit because few responses were answered, and few were not. Several vital questions went unanswered, linking to industry segments not primarily represented. Assumptions about dominant practices could introduce type nth errors, and firm-specific factors, such as economic conditions, are treated confidentially, complicating interpretation (Hernán et al., 2004). Complete sampling remains a critical challenge—limited generalizability arises due to low sampling saturation and the model's misfit (Biau et al., 2008; Heilala et al., 2023a). Without ideal sampling, the study's statistical validity hinges on employee indices but describes the actual statistics rigorously. The emphasis on firm-level effects and the focus on SMEs mark the need for a comprehensive analysis. The gathered data marks the importance of tracking changes between 2019 and 2021 and confirming supply chain impacts (Lakens, 2013).

5.2 Key findings and conclusions

The derivated extraction from the study of the sample using the EMS22 was challenging to analyze or hypothesize. In Finland, this research has never been carried out to the level of a research publication according to the research databases, expecting complexity to refer to the previous scientific, non-indexed frameworks not found. Thus, study implications make the organizations' contours and sustainability levels visible on the measurement interval. From the outset, the structural equation modeling had the most work for establishing the perspective to rely upon with partners, industry, and other stakeholders' publications. Concluding structural paths, the relationship between the manufacturer's portfolios and the development of competitiveness and employment factors is simple. Among business innovation models, product-related services and production organization demonstrated strong associations. Thus, the sample's firm business progress toward Industry 4.0 reliably predicts specific key performance indication that is not assessed for performance in this extraction, including business innovation models (particularly access and turnkey innovative economies), regular organizational concepts, and certain variables under product-related services (namely maintenance and repair and takeback services). Marking the end with extracting production control functional manufacturing execution systems, automation, and robotics shows a strong foundation for withdrawals. The study revealed that the manufacturing systems' access is thus enough through proper control.

Nevertheless, digital services, cybersecurity practices, efficiency technologies, simulation, data analysis, and additive manufacturing were rare. Roughly under one-tenth of the firms only significantly integrated into the betterment of the development of competitiveness and employment, pointing to possible areas of improvement and implementing future research and technology management. In contrast, the measures for regional expansion among sample firms were rare; the conclusion is a potential need for reassessment for significant strategic changes, whether to improve locally and also expand abroad for future research into locations not explored but popular with higher technology than within Europe, also considering lower technology regions. The study augmented resolution for advanced engineering to inspire the small sample size. With the limitations of the sample, the findings provide valuable marks for developing competitiveness and employment within the sample, contributing to future research directions. Further investigation stresses the importance of manufacturers reconsidering the service focus and domestic-based operations for organizations to adopt efficient multi-criteria decision-making technologies for product development stages.

5.3 Implications for the science and operations management

Scientific implications show digitalization and automation increase efficiency, real-time communication, and efficient resource allocation while shaping organizational structures. However, decreased cost adaptability and backshoring pressures from constraints pose challenges for near-term. *Sustainability* is a broader concept aligned with managerial industry guidelines requiring business operations adaptation with generative artificial intelligence integration. Internal and outsourced innovation enables transitions, updating job roles, learning, and training while the qualification of the integrationist requires new qualification requirements.

The study findings have notable implications for the participating cohorts. Fundamentally, business innovation models, product-related services, and organizational concepts necessitate emphasis, given the robust associations with digitalization uncovered in the research (Heilala et al., 2023a). As manufacturers, reevaluation of business models and regional expansion strategies proves warranted based on the study's revelation of limited expansion among firms (Heilala et al., 2023a; Heilala et al., 2022).

Certain technologies stand out as requiring additional adoption to enhance digitalization. Production control systems, automation, and robotics are substantially linked to digitalization, indicating the need for novel integration requirements (Heilala et al., 2023b). However, the lack of meaningful simulation, data analytics, and additive manufacturing implementation in some firms' digitalization efforts suggests that these advanced technologies mandate reassessment and tailored integration for certifications (Heilala et al., 2023a; 2023c). Beyond technologies, comprehensive workforce training and development focused on digital skills emerge as critical for manufacturers (Heilala et al., 2023b). Multi-criteria decision-making techniques, for instance, further enable efficient and sustainable production processes (Heilala et al., 2023a).

At the governmental level, the study denotes private actors' primacy in development and investment in certain regions. Human impacts like energy sector emissions contribute markedly to manufacturing efficiency, underscoring the necessity of governmental initiatives in project funding and cross-sectoral coordination (Asian Development Bank, 2012). Global energy market alignment with decarbonization in the 21st century reflects the potential for emissions reduction through policy (International Energy Agency, 2022).

With workforce composition instrumental for manufacturers, migration policy holds substantial implications. Proactive, flexible practices tailored to industry needs to drive economic growth, innovation, and job creation (Hogeforster & Wildt, 2021). Rethinking residence permit constraints and enabling immigrant entrepreneurship prove critical for growth (Hogeforster & Wildt, 2021). Historical and economic factors shape migration patterns, often involving highly skilled labor; targeted migration strategies offset regional knowledge and managerial gaps (Hogeforster & Wildt, 2021).

5.4 Recommendations for future research

The manufacturing sector requires continuous longitudinal research integrating larger samples and variables to study temporal changes related to future business needs. Comparative research between countries provides insights into the global impact of different operations models on Industry 4.0 to 5.0 competitiveness and employment (Hogeforster & Wildt, 2021). Supply chain simulations reveal how changes in contract and human resource practice affect competitiveness and employment development. Further research should explore inconsistent advanced technology integration impacts on competitiveness sustainability by studying energy management adoption and funding options (Hogeforster & Wildt, 2021). Regional economic incentives benefited the manufacturing sector's marketing, as explored by Hogeforster and Wildt (2021). Investigating sociocultural leverage, branding strategies, and labor conditions could help retain skilled employees. Exploring new areas helps understand the manufacturing sector's contribution by integrating sustainability practices for regional economic growth. Studying new organizational requirements is needed as digital transformation strategies evolve horizontally (Gurcan et al., 2023). Firms' adoption of efficient technologies with AI integration and converting manufacturing into sustainability strategies warrants operational research. The focus extends to exploring social sustainability aspects at an Industry 5.0 level as Industry 4.0 trends decline (Gurcan et al., 2023).

Specific organizational and technology concepts like production organization, production management and control, and competency development generally impact creativity and competitiveness in employment, requiring observation (Dul & Ceylan, 2014; Heilala & Krolas & Gomes de Freitas cited Heilala, Salminen, Bessa & Kantola 2023). Promoting efficiency technology and AI innovation adoption related to competitiveness and employment requires further study (Bendoly, 2016) fully. Exploring innovation laggards' sustainability and competitiveness productivity in manufacturing supports research on employee well-being, community impact, and ethical supply chains (Ferraris et al., 2018; Kopnina & Blewitt, 2014).

6 Conclusion

The empirical analysis validated that integrating production control systems like manufacturing execution systems (MES) and product lifecycle management (PLM) software with automation industrial robots leadsing to significant improvements by reframing high-performance work systems theory empirically out of manufacturing performance metrics. The models exhibited high accuracy, precision, recall, and F1 scores, confirming the reliability of the decision boundaries and predictive capabilities.

Nonetheless, the adoption levels of some advanced technologies, such as simulation, data analytics, and additive manufacturing, were relatively low across many of the surveyed manufacturing firms. This underscores an opportunity to integrate these technologies further to enhance advancing Industry 5.0 through additive manufacturing and technology integration.

The breakdown also uncovered full-bodied associations between business innovation models, product-related services like maintenance/repair, and organizational restructuring concepts with the degree of digitalization executed by manufacturers. Firms making more progress on digitalization tended to exhibit more vital key performance indicators in these areas.

At the same time, expansion into new regional markets was relatively rare among the sample firms, suggesting potential areas for strategic growth through relocation of manufacturing activities and R&D efforts tied to growing supply chain dynamics.

Workforce training and skills development, particularly around digital competencies, were highlighted as critical for manufacturers to capitalize on advanced technologies and adapt rapidly to balance future intelligent factory climates.

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Original Publications

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Optimizing smart factories: A data-driven approach.
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Optimizing Smart Factories: A Data-Driven Approach

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Since the first industrial revolution, the leading role of emerging technologies has been highlighted in modernizing the industry and developing the workforce. This study explores the impact of Industry 4.0 digital technologies on manufacturing competitiveness, focusing on Finnish SMEs within the EU with a sample (n = 123). It utilizes extensive 2022 European Manufacturing Survey (EMS22) data. Advanced statistical techniques reveal complex connections between automation, competitive edge on services, and innovation models, among other factors. Robust statistical methods, including component and reliability analyses, reinforced the findings. The conclusion offers critical insights and identifies areas for further research in combining innovative manufacturing practices with technology education.

Keywords: Industry 4.0; Competitiveness and employment, Supply chain contracts, Human Resources, Training and competence development, Business innovation model, Digital Services, Digital elements, Product related services, Cybersecurity practices, Key enabling technologies, Organization concepts, Relocation activities, Factor Analysis,

Introduction

This study's central motive is to quantitatively assess the impact of Industry 4.0 digital technologies on manufacturing competitiveness, specifically within the context of European Union Finnish small and medium-sized enterprises (SMEs). The alignment within the EU's strategic priorities is to modernize industry. Preparing the workforce in education and training means examining how technologies like automation and robotics applications can be integrated and leveraged. By utilizing the European Manufacturing Survey 2022 (EMS22) dataset tailored to the Finnish manufacturing sectors, the study aims to gain granular insights into SMEs' adoption and use of the manufacturer's key enabling technologies. The quantitative analysis of survey data provides data-driven perspectives to inform decision-making for Industry 4.0 integration.

The manufacturing industry has undergone significant transitions over centuries, from the advent of steam power and assembly lines in the 1750s (Industry 1.0) to the rise of global supply chains and localized production goals (Industry 2.0), and then progressive automation and digitalization since the 1960s (Industry 3.0). These advances have been driven by innovation and connectivity needs (Heilala, 2022). Today's environment demands extreme customization and efficiency. This motivates embracing technologies like automation and robotics, moving towards Industry 4.0. Such technologies are critical for European Union (EU) small and medium-sized enterprises (SMEs) to bolster competitiveness. The EU aims to strategically modernize industry and develop workforces for the future (Heilala, 2022).

This research utilizes the EMS, which has tracked Europe's industrial progression for two decades, offering a rich dataset. The EMS is an extensive survey conducted across European countries that collects key information on manufacturing strategies, technologies, and practices. It provides valuable insights into the state of the industry and how it is evolving amidst digital transformation and Industry 4.0 trends. The EMS adopts a broad perspective on manufacturing evolution, complementing the innovation-focused Community Innovation Survey (CIS) grounded in the OSLO framework (Consortium for the European Manufacturing Survey 2020; Dachs & Zanker, 2015; European

Commission et al., 2015). The refined EMS22 survey shows, by each question, The quantified variables of a representative sample of 123 small firms. As per leveraging EMS data, the impact of digital transformation on competitiveness is analyzed. The analysis applies exploratory factor analysis, structural equation modeling, and logistic regression to evaluate variable relationships on testing proposed hypotheses to form the logistic regression model. Key results reveal complex interdependencies between innovation models, technologies, services, and performance. The discussion interprets these insights, outlining empirical connections found and limitations encountered. The statistically driven findings contribute to the discourse on digital competitive advantage, providing a modeling foundation for ongoing research into optimizing smart manufacturing implementation.

Literature review - Decade-Long Perspective

Analytical review of manufacturing research trends

Prior EMS-based studies have utilized diverse statistical methods to analyze the survey data. The scoping review includes component analysis, reliability analysis through alpha, rho, and omega, and exploratory and confirmatory analyses. Structural path analysis shows multivariate analysis for discriminant and convergent validity assessments to implement in response to information characterization. Prior studies have shown depth in trade (European Commission, 2016; Kinkel et al., 2015). The lookup followed the format 'TITLE-ABS-KEY ("manufacturing" AND "statistic method")' to identify publications similar in the metadata. Results were filtered by year (2013-2023) for trends in Figure 1. The usage of each component's method used in manufacturing literature (2013-2023) needed to be more extensive. The internal structures' lower reliability frequency and the current research gap were identified.

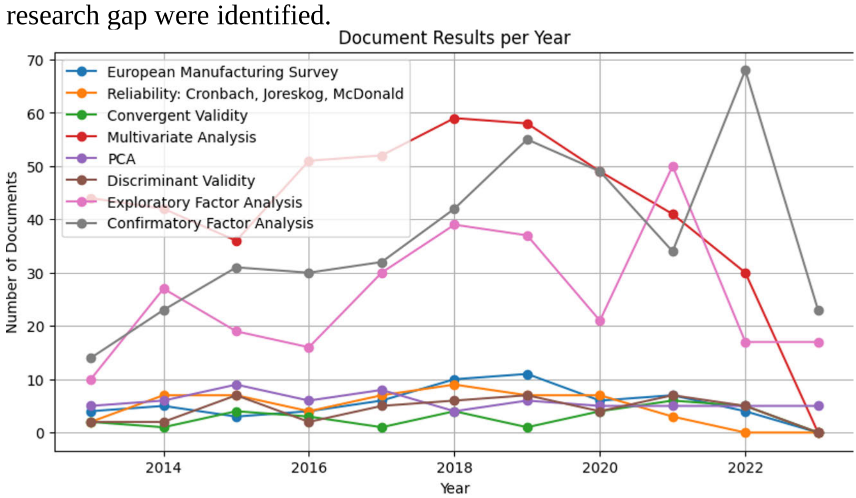

Figure 1: Trends for the statistical methods used in manufacturing method studies (2013-2023) (Scopus 2023).

While the analysis criteria development established the management domain, the gap in examined publication trends is shown. The scope highlights increased utilization of exploratory and confirmatory factor analysis while other areas decline. The current study is aligned with the use of pre-defined variables from key themes from the EMS 2022 survey to fill the gap. The analysis incorporates a meta-level surfacing the variables from the EMS2022 survey across categories, including competitiveness and employment metrics, supply chain contracts, human resources distribution, training initiatives, business innovation models, implementation of digital services, adoption of digital elements, provision of product-related services, cybersecurity practices, utilization of key enabling technologies, organization concepts, and prevalence of relocation activities abroad (Table 1).

Table 1 The study's classification development baseline adapts to EMS22 statements, testing if the practice is used for the context frameworks (EMS, 2022). The questions on the development of competitiveness and employment (DCES) are measuring manufacturing digitalization, acronymized as European manufacturing survey's (EMS's) key enabling technologies (KETs); organizational concepts (OCs) for relocation activities (RAs); digital services (DSs); cybersecurity practices (CPs) from the supply chain contract (SCCs) and resources (HR) perspectives. This shows that each of the factors explained is emerging in the experimental factor analysis addressed sample.

Category	Variables
Competitiveness and Employment	Annual turnover, number of employees, manufacturing capacity utilization, return on sales, investments in equipment and machinery, annual payroll as percentage of turnover, year of establishment
Supply Chain Contracts	Manufacturers, suppliers, contract manufacturers
Human Resources Distribution	University/college graduates, technically skilled workforce, trained workforce, semi-skilled and unskilled workers, trainees each segment indicating that practical skills and in-house training are highly valued in the workforce.
Training Initiatives	Task-specific training, cross-functional training, support in digital implementation, data security and compliance training, creativity, and innovation training
Business Innovation Models	Distribution, access, maintenance service-based, high-performance computing, on-demand, sharing, performance, and turnkey innovative economies
Digital Services Implementation	Customer contact platforms, digital standard solutions, automated customer interactions, remote access control elements, cloud and IoT solutions, big data analysis
Digital Elements Adoption	Identification tags, sensor technology, interactive interfaces, real-time network connection, digital transformation technologies
Product-Related Services Provision	Installation and start-up, maintenance and repair, training, remote support, design and project planning, prototype development, revamping and modernization, take-back services, software development
Cybersecurity Practices	Data security awareness, software solutions, hardware solutions, organizational measures
Key Enabling Technologies Utilization	Production control, automation and robotics, efficiency technologies, simulation, data analysis, additive manufacturing
Organization Concepts	Organization of production, management, and control, such as lean management, quality circles, and continuous improvement processes highlight the significance of organizational culture and structure in driving performance and adaptability.

Sustainable manufacturing is the creative process of synergizing the supply chain components. The enhanced competitiveness is a sign of good manufacturing for maintaining operations. It is reflected in key EMS variables related to innovation. Innovativeness requires automating human capital development for efficiency (Chia-Yen & Andrew, 2015; Mehta et al., 2010). Aligning with Europe's 2020 strategy goals, the Scopus review has limitations to the latest EMS data. Studying and assessing relationships between digital transformation, competitiveness, and employment within Finnish manufacturing is a top priority (European Commission, 2014).

Research hypothesizes

The review preliminaries show eight hypotheses developed to align with the analysis methods subsequently presented in the literature. The hypotheses show predictive relationships between EMS22 survey variables and manufacturing competitiveness and employment status for managing new natural law for technologist implications. The analysis tests hypotheses on the influence of EMS variables related to competitiveness and employment metrics (integer/binary), which are

H1. Business innovation model variables

H2. Digital service implementation variables,

H3. Digital element adoption variables,

H4. Product-related service provision variables,

H5.Cybersecurity practice variables,
H6.Key enabling technology utilization variables,
H7.Organization concept variables, and
H8.Relocation activity variables, that

Have an explicit connection to Finnish manufacturers' competitiveness and employment. Anonymization was applied to model the small enterprises on the modeling path for a general overview. Competitiveness and employment status show the sample balanced challengingly with various sectors. The general model of the multivariate analyses between variables is usable for remote measurement of the firm floor-level relationships when fitted with normalized scores. The hypotheses assume the specific hypotheses of connections explore the exploratory model and the bottom-level quotes to converge for discussion. Thus, the literature review of analysis methods considers exploratory factor analysis to assess the underlying factor structure. The measurement models against the survey data follow the factor structure evaluation. Structural path visioning shows the Tested hypothesized relationships advantaged to classify the sample. Reliability analysis for discriminant and convergent validity assessments validates the construct's internal validity. This EMS data derives the measure to manage small chains by a quantitative approach aligned with analyzed studies.

Multi-analytic Research Methodology

Over time, the manufacturing studies trends from Scopus show applications to analyze manufacturing survey data. Findings of analyses type sorted (e.g., Kinkel et al., 2015; European Commission, 2016). A requirement to utilize factor analysis with structural path analysis is to establish an augmentation to explore relationships between variables from the latest EMS data. As such, explorative factor analysis is applied to assess the underlying factor structure with linear regression. The confirmatory on-path evaluation shows the measurement models on the survey data to the lagged binary correspondence. This was adapted to logistic regression with industry responses, reporting reliability to the causal treatment domain, see, e.g. (Wang et al., 2020; Gomila, 2021). For the detailed analysis, with the depth of linear analyses, utilizing logistic regression helped deal with binary data for drawing dedicated results. The grounding is considering traditional model fit indices for likelihoods. The accuracy on the analysis-dependent level is usually based on statistical principles (Hilbe, 2009; Casella & Berger, 2002; Hosmer Jr. et al., 2013). The approach offers coefficient interpretation in terms of associations between the variables studied. The regression path shows the hypothesized relationships influencing manufacturing competitiveness and employment component space. Reliability analysis shows internal consistency (Taber, 2016). discriminant and convergent validity validated in further models of measurement (Anderson & Gerbing, 1988).

Data-analysis

A sample (n=123) encompassed diverse industrial classifications to capture a breadth of product types and business models as classified (Heilala & Krolas, 2023). The data was acquired through Webropol's natural language collection tool and underwent cleaning to remove irrelevant responses (Webropol, 2022). The refined dataset was coded for frequency, reliability, and component analyses. Reliability analysis of the EMS2022 constructs was used to reveal internal consistency values. For reliable data, a partial technique across Industry 4.0 sectors established interpretable results (Bozgulova & Adambekova, 2023; Juariyah et al., 2020). Utilizing over 50 sub-items from the EMS22 survey represents a framework. Analysis of growth strategies in manufacturing, focusing on technologies, practices, and their impact on competition and employment industry-wide.

This spectrum of the manufacturing sector shows' manufacturing of metal products and 'Manufacturing of machinery and equipment,' and the software sector is most prominent. Industry sectors held a more miniature representation on each side for diversity and possibilities (Heilala & Krolas, 2023). The manufacturing industry studies have not been interested in industry-wide participatory studies (EMS, 2022; European Commission et al., 2015). Participation is included in the varied scope of industrial manufacturing, from factory assemblies to comprehensive lifecycle process assessments. Studies have usually served customers with platform requirements, such as within construction industry (He et al., 2018).

Convergent and congeneric reliability levels

Component analysis was used for dimensionality reduction to measure the reliability of constructs. The Cronbach Alpha, Jöreskog's Rhô, and McDonald's omega were followed as in Table 2 (Taber, 2016). Alongside the analysis of several items (survey questions or statements used), the measures of internal consistency indicate a set of items' interrelation. A higher value suggests that the items measure the same concept.

Table 2: Construct reliability levels show higher reliability for constructs, abbreviations explained below, indicating strong internal consistency with high measurement accuracy.

	Items	Cronbach's Alpha	Joreskog Rhô	McDonald's Omega	val.
DCES	4	0.900	0.803	0.867	62
BIMs	6(7)	0.765	0.530	0.505	59
DSs	6	<.50	<.50	<.50	88
PRS	17	.825	0.824	.839	105
DEs	5	.799	0.865	.812	106
CPs	4	<.50	<.50	<.50	105
KETs	18	0.951	0.595	0.755	123
OCs	11	0.803	0.889	0.659	120
RAs	3(4)	0.900	0.885	0.583	80

Several constructs in Table 2 exhibit poor reliability per the coefficient values below 0.5. In the stats table, DCES (developing competitiveness and employment stats) measures various aspects such as AT (annual turnover) and NE (numbers of employees) to the other factory specifics, showing high reliability in all coefficients and suggesting it is a well-measured construct. On the contrary, BIM (business innovation models) has moderate reliability, indicating the varying degree of integration that could be the first varying signal of innovation potential within firms. Surprisingly, DSs (digital services) exhibit poor reliability, raising concerns over the effectiveness of these measures in capturing companies' digital transition. PRS (product-related services) demonstrated robust reliability across all coefficients for services provided, reflecting customer relationship on maintenance services. The high-reliability scores were affirmed for DEs (digital elements). Poor reliability for CPs (cybersecurity practices) has indicated potential issues in consistently measuring how digital infrastructure is safeguarded. Despite moderate reliability, KETs (key enabling technologies) benefit the omega display because it has a broad scope of moderate reliability measures regarding a few item combinations that align with each other. Similarly, but contrary to omega, OCs (organization concepts) present reliable measures contributing to firm efficiency and agility. Uniformity to globalization, RAs (relocation activities) exhibit varied reliability across coefficients. The first signal to the empty tabulations shows Heilala and Krolas (2023), who note that the carbon footprint in offshore locations needs to be more consistently optimized by reassessing certified systems.

Factor analysis

Despite a few constructs having insufficient reliability for further analyses, another angle to considering partial exploratory factor analysis (PEFA) was taken. PEFA was an intriguing option to form over an established, validated framework of the survey metrics. The technique has been used across manufacturing and other Industry 4.0 sectors, reliably increasing safety to select the analysis method (Bozgulova & Adambekova, 2023; Juariyah et al., 2020). Factor analysis provides insights into the multivariate relationships of survey instruments (Creswell, 2015; Edmonds & Kennedy, 2019). PEFA shows the interconnections between factors influencing the instruments (Matsunaga, 2010; Revelle, 2013). Rotation methods of VariMax and ProMax optimize factor separability (Matsunaga, 2010). The PEFA is shown in the Table 3 model DCES (developing competitiveness and employment situ) measures of annual turnover for 2019-2021 (AT19/21; m23a1, m23a2), employee numbers for 2019-2021 (NE19/21; m23b1, m23b2), capacity utilization for 2019-2021 (MCU19/21; m23h), return on sales for 2019-2021 (ROS19-21; m23i1-5), investments (m23f), payroll percentage (m23g), and establishment year (m23k) reflect financials, labor dynamics, asset efficiency. High turnover and employment correlate with competitiveness. Supply chain contract (SCC) types categorize operators as manufacturers (MFR; m03a1-a3), suppliers (SPLR; m03a4-a5), or contract manufacturers (CM; m03a6), capturing production system roles. Manufacturers' negative SCC correlation potentially signals inflexibilities, unlike positively correlated suppliers and contract manufacturers benefitting from dynamic agreements. Human resources (HR) distribution classifies graduates (m16a1), technical staff (sm16a2), trained workers (m16a3), semi/unskilled personnel (m16a4), and trainees (m16a5), measuring skills and qualifications. Graduates' negative HR correlation potentially reflects oversaturation, contrasting positives for vocational abilities. Business innovation models (BIM) like leasing (BIM1; m18a1), service contracts (BIM2; m18b1), output-based services (BIM3; m18c1), sharing models (BIM4; m18d1), availability guarantees (BIM5; M18e1), and turnkeys (BIM6; m18f1) integrate variably, signaling innovation potential. Digital services (DS) include standards solutions (m18g1), automated customer processes (m18g2), remote access controls (m18g3), cloud/IoT applications (m18g4), and data analytics (m18g5), enabling digital transitions. Digital elements (DE) such as identification tags (m04a1), sensors (m04a2), interactive interfaces (m04a3), real-time connections (m04a4), and IoT integrations (m04a5) emphasize digitization's role. Product-related services (PRS) spanning installation (m15a1), maintenance (m15b1), training (m15c1), support (m15d1), consulting (m15e1), prototyping (m15f1), modernization (m15g1), takebacks (m15h1), and software (m15i1) maintain customer relationships. Cybersecurity practices (CP), including awareness (m11a1), data controls (m11a2), network solutions (m11a3), and protections (m11a4) safeguard digital infrastructure. Key enabling technologies (KET) from programming devices (m09a1) to simulation software (m09p1) drive innovation and sustainability. Organization concepts (OC) encompassing integration (m06a1), customer-focus (m06b1), pull-based control (m06c1), changeover optimization (m06d1), standardization (m06e1), visual management (m06f1), quality assurance (m06g1), innovation involvement (m06h1), performance incentives (m06i1), environmental management (m06k1), and energy management (m06l1) contribute to efficiency and agility. Relocation activities (RA), including offshoring production (m26a1) and R&D (m26b1) and backshoring production (m26c1) and R&D (m26d1) represent strategic footprint optimization. The commonalities indicate digitalization's integral role and human capital's nuance in competitiveness, demanding tailored management. This statistical portrait outlines the drivers of European manufacturing competitiveness, employment, innovation, and strategy amidst Industry 4.0 transformation. (EMS, 2022.).

Table 3: The factor loadings offer a multidimensional perspective on the interconnected variables influencing European manufacturing as discerned from the EMS22 survey.

EMS item	DCES	SSC	HR	BIM	DS	DE	PRS	CP	KETs	OCs	RA	COM
m23a1	.937											.878
m23b1	.915											.836
m23h	.389											.151
m23i1-5	.261											.068
m23a2	.932											.869

m23b2	.920											.846
m23h	.419											.175
m23f	.514											.264
m23g	-.451											.203
m23k	.676											.457
m03a1-a3		-.909										.826
m03a4-a5		.522										.273
m03a6		.564										.318
m16a1			-.927									.860
m16a2			.190									.036
m16a3			.211									.045
m16a4			.677									.458
m16a5			.357									.127
m18a1				.332								.110
m18b1				-.144								.021
m18c1				-.081								.007
m18d1				.794								.631
M18e1				.795								.631
m18f1				.785								.616
m19a					-.612							.375
M18g1					.538							.290
m18g2					.153							.023
m18g3					.570							.325
m18g4					-.560							.313
m18g5					-.612							.375
m04a1						.768						.356
m04a2						.727						.590
m04a3						.858						.528
m04a4						.785						.736
m04a5						.597						.616
m15a1							.681					.463
M15b1							.625					.391
m15c1							.654					.427
M15d1							.602					.362
M15e1							.550					.302
m15f1							.482					.232
m15g1							.622					.387
M15h1							.208					.043
M15i1							.577					.333
m15a2							.598					.358
m15b2							.643					.413
m15c2							.499					.249
m15d2							.506					.256
m15e2							.436					.190
m15f2							.276					.076
m15g2							.360					.130
m15h2							.089					.008
m11a1								-.318				.101
m11a2								.617				.381
m11a3								.725				.525
m11a4								.509				.259
m09a1									.446			.199
m09b1									.448			.201
m09c1									.259			.067
m09d1									.496			.246
m09e1									.537			.289
m09f1									.466			.218
m09g1									.481			.232
m09h1									.560			.313
m09i1									.588			.345
m09q1									.536			.287
m09r1									.562			.316
m09k1									.665			.443
m09l1									.552			.304
m09m1									.581			.337
m09n1									.584			.341
m09o1									.452			.204
m09p1									.608			.369
M09q*									.516			.266
m06a1										.609		.370
m06b1										.595		.355
m06c1										.482		.232
m06d1										.570		.325
m06e1										.647		.418
m06f1										.532		.283
m06g1										.480		.230
m06h1										.613		.375
m06i1										.552		.305
m06k1										.555		.308
m06l1										.393		.155
m26a1											.699	.488
m26b1											.749	.561
m26c1											-.175	.031
m26d1											.751	.564

z-standardized; *Extra

Annual turnover and employee numbers (m23a1, m23a2, m23b1, m23b2) strongly correlate with the Competitiveness and Employment Status factor (DCES), underscoring their pivotal role in manufacturing prowess. Conversely, manufacturers (m03a1-a3) exhibit a negative relationship with Supply Chain Contracts (SSC), in contrast to the positive loadings for suppliers and contract manufacturers (m03a4-a6), revealing the complexities within supply chain dynamics. Human Resources (HR) are differentially impacted by the workforce composition, where graduates (m16a1) show a negative association, while technical, trained, semi-skilled, unskilled staff and trainees (m16a2-a5) present positive correlations, highlighting the multifaceted nature of human capital in this sector. The Business Innovation Models (BIM) spectrum (m18a1 to m18f1) demonstrates diverse associations, suggesting that innovation models integrate more seamlessly into the current industrial fabric. Digital Services (DS) and Elements (DE), illustrated by loadings for (m19a, m18g1 to m18g5, and m04a1 to m04a5), emphasize the growing importance of digitalization. Product-related services (PRS: m15a1 to m15h2), Cybersecurity Practices (CPs: m11a1 to m11a4), Key Enabling Technologies (KET: m09a1 to m09p1), Organization Concepts (OC: m06a1 to m06l1), and Relocation Activities (RA: m26a1 to m26d1) all display variegated correlations, indicating that specific practices, technologies, and strategies are differentially integrated and valued within the sector. Collectively, these loadings serve as a statistical map outlining how various elements contribute to the overall competitiveness, employment landscape, innovative capacity, and strategic direction of European manufacturing firms.

Convergent and discriminant validity

However, the PEFAs Tucker-Lewis (Tucker & Lewis 1973) indicated only partial reliability, as from the reliability in Table 2 a few chapters back elaborated. For consistency, the potential removal of some variables is suggested. The limit must be raised to elaborate the unrelated contribution of interrelations of arithmetic sums of the companies' characteristics studied (Revelle, 2013)—correlation (R) analysis to Table 4 further explored relationships between variables of interest. The data normalization Was applied to ensure compliance with the central limit theorem (Schober & Boer, 2018). This comprehensive analysis elaborates on variable relationships. Potential quadratic relationships were acknowledged. The quadratic or cubic terms are rare, highlighting the need for careful analysis to saturation (Robinson & Schumacker, 2009). The R shows that the internal reliability does not control the fluctuations of the company-dependent variables. There are no homogeneous groups unless market transformers are balanced in the manufacturing portfolio (Malik et al., 2023).

Table 4: R magnitudes average extractions; the factors are z-standardized

	ZDCES	ZBIMs	ZDSs	ZDEs	ZPRS	ZCPs	ZKETs	ZOCs	ZRAs
ZDCES	(0.25)								
ZBIMs	-0.063	(0.297)							
ZDSs	0.052	.324**	(0.283)						
ZDEs	.303**	.318**	0.219	(0.565)					
ZPRS	0.028	.419***	.371****	.658****	(0.41)				
ZCPs	0.007	0.256*	.910****	0.089	.205**	(0.317)			
ZKETs	.417***	-0.100	0.060	0.175*	0.047	0.042	(0.28)		
ZOCs	.418***	0.006	0.090	.248**	0.050	0.046	.655****	(0.31)	
ZRAs	0.077	0.022	0.085	.398***	.379****	0.023	.305***	0.214*	(0.41)

Note: results do not have significant relation/not connect (n.s./n.c.), ****p<0.001, ***p<0.01, **p<0.05 and *p<0.1.

Table 4 presents a matrix of R coefficients, which explores the relationships between pairs of z-scored variables representing different constructs (e.g., ZDCES, ZBIMs, ZDSs, etc.). Rs are showing the strength and direction of the relationships between constructs. The diagonal elements in parentheses indicate the average variance extracted for each construct, a measure of convergent validity that assesses the extent to which items of a construct are positively correlated. For instance, ZDEs and

ZPRS have a robust positive correlation (R = .658****), suggesting that as one construct increases, the other tends to increase as well, and this relationship is statistically significant at the p<0.001 level. Similarly, ZCPs and ZDSs are highly correlated (R = .910****), indicating a strong positive relationship with statistical significance.

Hypothesis testing

Table 5 presents the results of hypothesis testing, adding depth to the cross-correlations by direct multivariate measures to evaluate the fit of different models to the data. The models test specific hypotheses concerning the relationships between the introduced construct and other variables within the dataset. A high RMSEA (root mean square error approximation) suggests a poor fit between the model and the observed data, indicating the need for model revision. Despite model data fit limitations, the survey analysis is a complete, valid measure involving an extraordinary spectrum. The mediation model successfully depicted indirect effects on the resolution (Baron & Kenny, 1986; Frazier et al., 2004). For example, in biotechnology studies, multiple indices can be eliminated if a too-good fit becomes a highly restricted model (Lai et al., 2016).

Table 5: uses DoF (degrees of freedom), χ^2 (Chi-squared) test, and p-value for model evaluation. A p-value < 0.05 typically rejects the model fit. Ratios χ^2/df, and RMSEA show fit informing questionnaire validation.

Models	DoF	(χ^2)	p-value	χ^2/df	RMSEA*	Hypotheses Result
BIMs	21	61.636	<.001	2.92	Medium	Accepted for BIM2, BIM6; Rejected for others
DSs	10	N/A	>.05	N/A	High	Rejected for all (5)
PRS	153	497.613	<.001	2.47	Medium	Accepted for PRSO3, PRSO8; Rejected for others
DEs	10	170.463	<.001	17.463	Medium	Accepted for all (5)
CPs	10	N/A	>.05	N/A	High	Rejected for all (4)
KETs						Accepted for PC, AR; Declined for SDA, ET
	6	59.579	<.001	9.93	Null model	
OCs						Accepted for all (3)
RAs						Rejected for all (4)

*Note Low (>.07), null model (>.20), medium (<.20) or High RMSEA (<.30).
N/A (not applicable): not computed; lack of data.

The hypotheses result column reflects hypothesis testing outcomes within each model for having relative model fit indices based on what we have (Schubert et al., 2017). The consideration of industry requirements culminates in certifying operating boundaries in the globally recognized framework for management. The question of accepting or rejecting the sample rather than removing the sample size could be based on p-values and fit indices like χ^2/df and RMSEA with high factor loadings applicable to be studied. This would elevate the indices results due to limited saturation. As per medium models were found in the BIMs (business innovation models), specific hypotheses such as BIM2 (access) and BIM6 (turnkey project) having supported; product-related service (PRS) show PRS3 (training) and PRS8 (recycling/lifecycle of a product tracing); and for DE (digital elements) for all: DE1 (identification), DE2 (digital functions); DE3 (interfaces); DE4 (realtime-network); and DE5 (transformations). KETs (key enabling technologies) for AR (automation and robotics) with PC (production control) were supported, but other technologies like simulation, data analysis, and additive manufacturing were not. The OCs (organization concepts) spectrum showed affirmative. Table 5 shows that null modes were taken to the investigations to build a new model in discussion. The proposed automation and robotics technology management model was stable out of statistical biases. The industrial engineering management on automation and robotics robustness shows a technology model. Industrial Management's dilemma on perfect model fit corresponds to the highest expectations (Hogeforster & Wildt, 2021). The chi-square is not definitive in determining fit indices in understanding industrialized imbalanced segregations with indications (West et al., 2012; Shi et al., 2019). The hypothesized per a priori model is in Figure 2—the path drives key relationships. The figure's paths provide the research model's partial exploratory factor analysis elimination perspective. The figure proposes ln-not corroborated linkage to avoid worsening the model fit.

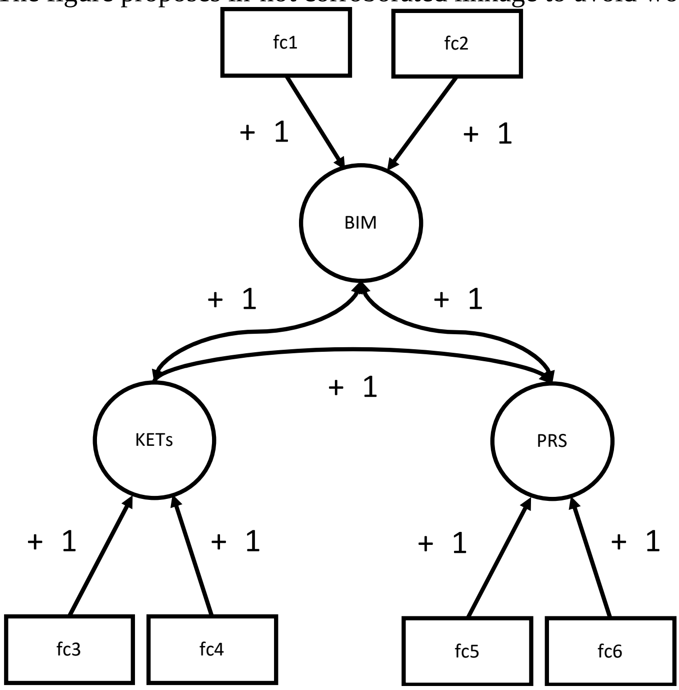

Figure 2. Has medium outlining for a null model for manufacturing survey results for discussion (arrows as causal hypotheses), focusing on contribution altogether, with BIMs with factors fc1-access and fc2-turn key innovation; KETs with factors fc3-automation and robotics and fc4-production control; and PRS, with factors fc5-online and fc6-maintenance provided —to achieve digital competitive advantage in Industry 4.0. Solid arrows depict validated causal connections between variables and factors, while double-headed arrows represent bidirectional correlations among BIMs, KETs, and PRS.

Refining empirical variables

The refined structural multivariate hypothesis test shows evidence for support. Proposed relationships in the explorative research model are merged. Automation and robotics technologies computed dependent variables. Given the guess. Given their increasing prevalence in smart factories (Wang et al., 2020). This will allow testing of the integration between production control software and automated/robotic management. Per Manufacturing execution systems (MES, m09g1) and product lifecycle management (PLM, m09f1) selection to the independence of production control systems. The integral components of digital manufacturing infrastructure were explored (Lee et al., 2022). Shall MES and PLMs be selected for real-time data collection, monitoring, quality management, and product lifecycle data management (Zhong et al., 2021)? As per demonstration affirmative. The maintenance model into performance could also be critical for manufacturing operations review (Grieco et al., 2022). The result identifies MES and PLM enabling the transformation forward for Industry 4.0 (Capgemini Research Institute, 2021).

Empirical results

Structural concept

Per linear analysis: the depth included methods for causal links and chained handling of binary data, providing logic for advanced manufacturing (Heilala & Krolas, 2023). The logistic analysis is flexible per practice contract. Figure 3 shows that managed business innovation models (BIMs) and product-related services (PRS) can be abandoned. Industry 4.0 emphasizes manufacturing production control, automation, and robotics as key enablers. This framework for competitive advantage dynamics is in Figure 3.

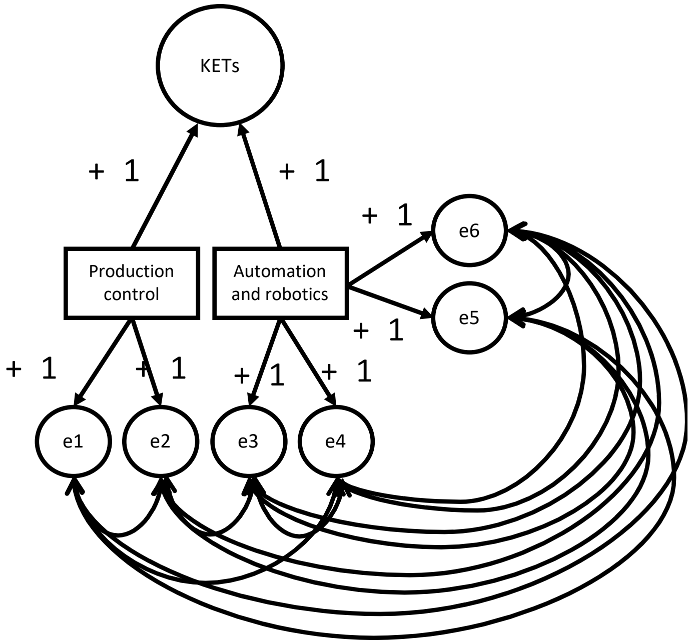

Figure 3. Structural models illustrate the a priori linear relationships between automation and robotics production control endogenous variables (e1-e6, m09, and m23-series with financial management in EMS).

Exclusions of most of the factors were due to data constraints-imposed model. The boundary limitations for the power analysis on a small square are visible. Yielding lower RMSEA for fit between production control, automation, and robotics technologies. The correlates in m09-series endogenous variables e1 (f1) and e2 (g1), and connections to e3 (h1) and e4(i1) were highlighted. Integrating advanced technologies as foundational for Industry 4.0's competitive positioning evokes the primary hypothesis. The cross-sectional innovative servicing of robots and automation also linkages with e5(q1) and e6(r1) can validate hypotheses. Confirmatory analysis suggests that innovative business practices leverage m09-series digital capability. This implies refined performance strategies resulting in manufacturer-minimum classification. The pathways of the manufacturer show solid arrows for empirically supported hypotheses, as regression ruling demonstrates. Growth stimulates advancement in other elements without the requirement for simulation. The selection variables support the theoretical hypotheses in Table 7 (Appendix A).

Table 7: The examination of a logistic regression model showing linear as detailed in Appendix A with A.1, merging various metrics of model performance with validation; A.2 measuring the model predicting correct outcomes; A.3-A.4 the model's accuracy to the relationship with result predictions.

	precision	recall	f1-score	support

	0.0	1.00	0.71	0.83	7	
	1.0	0.88	1.00	0.93	14	
	accuracy	0.90	21			
	macro	avg	0.94	0.86	0.88	21
weighted	avg	0.92	0.90	0.90	21	

The logistic regression predicts the fusion of automation technology with performance metrics. The characteristics of manufacturing classification accuracy elucidated precision to continue scientific discussions of applied regression's (Hilbe, 2009; Casella & Berger, 2002; Hosmer Jr et al., 2013). the analytical strategy's novelty shows reliability and discourse to literature to transform it into transformative innovation for engineering and financial management. Execution and lifecycle systems were chosen to represent the production of automation and robotics. These are integral components of digital manufacturing infrastructure for sustainability (Lee et al., 2022). These systems offer comprehensive capabilities for real-time data collection, monitoring, quality management, and product lifecycle data management (Zhong et al., 2021). Past research shows similarities in shipbuilding (Sánchez-Sotano et al., 2019). Execution systems dimensioning without what operations are left to the heavy organization procedures irrelevant to manufacturers. Leading industry reports also identify results essential in digital transformation enablers for Industry 4.0 (Capgemini Research Institute, 2021). Regressions in measuring the literature confirmed a similar significant positive correlation between integrated execution on the production lifecycle, and it is being integral to finance.

Discussion

This study utilized path analysis and logistic regression to examine relationships between key manufacturing technologies and production outcomes. The analysis focused on widely adopted technologies and their interactions with automation and robotics. Positive correlations were found between these variables, validating hypothesized beneficial technology integration effects. While data limitations prevented confirmation of all proposed relationships, the statistically supported linkages represent essential findings for a refined model concentrating on validated connections to enable intelligent manufacturing performance.

The study also analyzed survey data assessing connections between digital transformation, manufacturing competitiveness, and employment in Finland. While hypothesis testing yielded mixed results, complex interrelationships, some business models and technologies exhibited clear positive ties to improved competitiveness. Furthermore, interactive interfaces, real-time networking, and digital transformation adoption are related to better competitiveness and employment scenarios (Moeuf et al., 2017). However, more than transparent or insignificant relationships were found for other variables like digital services, cybersecurity, simulation tools, and additive manufacturing (McNeish, 2018). These highlight areas needing further research before emphasis or investment.

Conclusion

A statistical factorization outlined manufacturers' contributions from 2019 to 2021. The science gap reaches integration into European manufacturing competition, which concludes with execution and lifecycle management. According to the original hypotheses, growth has complex interdependencies. The inevitable other elements correspond to the performance outcomes. However, the study cannot decide which principles of execution and lifecycle should prepare manufacturing. The standpoint on usable data constraints limited full confirmation. A partial overview supports every hypothesis. However, it is rare for a company to afford a complex system and business when manufacturing must be planned separately. A couple of more prominent companies with higher turnovers have higher integrative posts.

In conclusion, this study utilized statistical modeling to analyze the relationships for competitive manufacturing. Findings confirmed automation, robotics, and production control integration for performance. However, emerging technologies showed unclear impacts, requiring a reliable network. While small datasets set limitations preventing full spectral confirmation to all hypotheses reliably, responses contribute to future research and development. The database meta-analysis on the factor analysis' reliability reporting could be interesting to address in further studies. Factor analysis root means a square error has been outlined as heterogeneous, to which homogeneous generalization researchers aim to keep science differentiated from the actual practice. At the same time, others seem not to report indices. The indicative meta-analysis with regression test differentiates items and could open the industry trends, improving high indices.

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APPENDICES

Appendix A: Evaluation of Logistic Regression Model Outcomes

Figure A.1: Integrated Display of Model Performance Metrics

Figure A.2: Receiver Operating Characteristic (ROC) Curve Demonstrating Outcome Predictive Efficacy

Figure A.3: Histogram and Bar Plot Analysis Detailing Precision, Recall, and F1-Score for 'FF' and 'TF' Outcomes

Figure A.4: Scatter Plot with Trend Line for Model Support Against 'Outcome' Categories

Appendix A: Evaluation of Logistic Regression Model Outcomes

```
import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score, classification_report

data = { 'AT_m23a1': [-99, -99, -99, -99, 0, -99, -99, -99, 1, -99, -99, -99, -99, 113, 13, -99, -99, 1, 2.1, -99, 6, 6, 65, 8, 1, 2, -99, 29, 1,
16, 4, -99, 12, 4, 1, 7, 339, -99, 24, -99, 3, 59, 29, 24, 1, 10, 3, 10, -99, 70, 3, -99, 17, 2.4, 17, -99, -99, 3, 1, -99, 48, 2, 2.8, -99, -99, -99,
120, 10.8, -99, -99, 3.022, 0.6, 3, 45, 1.5, 1.2, -99, 1, -99, 5, 0.432, 4.7, 1, 9.7, 2, -99, -99, 1.2, 2, 12.397, 100, -99, 1.04, 2.2, -99, 32, 80,
220, -99, -99, 6, -99, 19.586, 11, -99, 6.26, 9.3, 6.4, 110, -99, 6, 1.7, -99, -99, -99, -99, 3.096, 6.2, 55, 0.4, 128, 82.295749 #… all others],
'AT_m23a2': [-99, -99, -99, -99, 0, -99, -99, -99, 1, -99, -99, -99, -99, 105, 11, -99, -99, 1, 1.6, -99, 7, 6, 60, 6, 1, 1, -99, 38, 1, 15, -99, -
99, 11, 5, 0, 9, 326, -99, 22, -99, 20, 63, 24, 24, 1, 9, 2, 12, -99, 49, 2, -99, 15, 0.6, 15, -99, -99, 2, 1, -99, 32, 1, 2.7, -99, -99, -99, 120,
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others],
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150, 54, 10, 42, 4, 55, -99, 220, 30, -99, 50, 21, 110, -99, -99, 6, 12, -99, 65, 19, 15, -99, -99, 43, -99, 300, 120, 230, -99, 20, 26, 3, 240,
11, 6, 12, -99, 100, 7, 17, 12, 57, 11, 20, -99, 17, 20, 65, 280, -99, 14, 10, -99, 65, 160, 500, -99, -99, 42, -99, 99, 60, -99, 51, 34, 76, 300,
200, 80, 12, -99, 75, -99, -99, 25, 43, 190, 4, 52, 75, 20, 120, 140, 90, 14, 54, -99, -99, 5, 47, 9, 4, 54, 5, -99, 45 #… all others],
'NE_m23b2': [-99, 12, 2, -99, -99, 14, 14, -99, 38, 28, 64, 18, 7, 13, -99, 240, 17, 105, 33, -99, 44, 18, 8, 51, 320, -99, 33, -99, 8, 175,
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190, 78, 11, -99, 70, -99, -99, 24, 40, 185, 3, 50, 73, 19, 116, 135, 88, 12, 52, -99, -99, 4, 45, 8, 3, 52, 4, -99, 42 #… all others],
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0, 0, 0, 1, 0, 0, 0, -99, 0, 0, 1, -99, 1, 1 #… all others],
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99,1,-99,1,-99,-99,-99,1,-99,-99,1,0,-99,0,-99,1,-99,-99,-99,-99,-99,1,-99,1,1,1,0,-99,1,0,-99,-99,-99,1,-99,1,1,-99,-99,1,-99,-99,1,0,1,1,-
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'AR2_m09i1': [0,0,-99,-99,1,0,-99,-99,-99,-99,0,0,-99,1,-99,-99,0,-99,-99,-99,-99,-99,-99,-99,-99,0,-99,0,-99,-99,1,-99,-99,0,-99,-99,-
99,0,-99,0,-99,-99,-99,0,-99,-99,1,1,-99,1,-99,0,-99,-99,-99,-99,-99,0,-99,1,0,1,1,-99,1,0,-99,-99,-99,0,-99,0,1,-99,-99,0,-99,-99,0,1,1,0,-
99,1,0,-99,-99,-99,-99,0,-99,1,0,-99,-99,1,-99,-99,-99,0,-99,-99,1,1 #… all others],
'AR3_m09q1: [0,0,-99,-99,0,0,-99,-99,-99,-99,1,1,-99,0,-99,-99,0,-99,-99,-99,-99,-99,-99,-99,-99,0,-99,0,-99,-99,0,-99,-99,1,-99,-99,-
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99,0,0,-99,-99,-99,-99,0,-99,0,0,-99,-99,0,-99,-99,-99,0,-99,-99,0,1 #… all others],
'AR4_ m09r1': [0,0,-99,-99,0,0,-99,-99,-99,-99,0,1,-99,0,-99,-99,1,-99,-99,-99,-99,-99,-99,-99,-99,0,-99,0,-99,-99,0,-99,-99,0,-99,-99,-
99,0,-99,0,-99,-99,-99,0,-99,-99,1,0,-99,0,-99,0,-99,-99,-99,-99,-99,0,-99,0,0,1,1,-99,0,1,-99,-99,-99,0,-99,0,0,-99,-99,0,-99,-99,0,1,1,1,-
99,0,1,-99,-99,-99,-99,0,-99,0,0,-99,-99,0,-99,-99,-99,0,-99,-99,0,1 #… all others] }

df = pd.DataFrame(data)

df.replace(-99, pd.NA, inplace=True)

for col in df.columns:

    mode_val = df[col].mode()[0]

    df[col].fillna(mode_val, inplace=True)

X = df[['MES', 'AT_m23a1', 'AT_m23a2', 'NE_m23b1', 'NE_m23b2', 'AR1 m09h1', 'AR2 m09i1', 'AR3 m09q1', 'AR4 m09r1']]

y = df['PLM']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

clf = LogisticRegression(max_iter=1000)  # max_iter

clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)
```

Figure A.2: Receiver Operating Characteristic (ROC) Curve Demonstrating Outcome Predictive Efficacy

```
import numpy as np

from sklearn.metrics import precision_recall_fscore_support, roc_curve, auc

import matplotlib.pyplot as plt

import seaborn as sns

df = pd.DataFrame(data) # As given

df.replace(-99, np.nan, inplace=True)

df.dropna(inplace=True)

X = df[['PLM', 'MES']]  # PLM & MES as features

y = df['AR1']  # Assuming for example, that 'AR1' is the target variable

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

logreg = LogisticRegression()

logreg.fit(X_train, y_train)

y_pred = logreg.predict(X_test)

y_pred_proba = logreg.predict_proba(X_test)[:,1]

accuracy = accuracy_score(y_test, y_pred)

precision, recall, f1, _ = precision_recall_fscore_support(y_test, y_pred, average='binary')

report = classification_report(y_test, y_pred)

print('Accuracy:', accuracy)

print('Precision:', precision)

print('Recall:', recall)

print('F1 Score:', f1)

print('Classification Report:\n', report)

fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

roc_auc = auc(fpr, tpr)
```

Figure A.3: Histogram and Bar Plot Analysis Detailing Precision, Recall, and F1-Score for 'FF' and 'TF' Outcomes

```
# Plotted normalized data

data = {     # 'Y': [5.5, 6.7, 8.8, 4.4], # Interface

    'AT_m23a1': [1, 2, 3, 4], # Growth for 2021

    'AT_m23a2': [2.1, 2.2, 2.3, 2.4], Growth for 2019

    'NE_m23b1': [3, 3.1, 3.2, 3.3], # Size for 2021

    'NE_m23b2': [4, 4.1, 4.2, 4.3], # Size for 2019

    'AR1 m09h1': [5, 5.1, 5.2, 5.3], # Industrial robots for manufacturing adoption

    'AR2 m09i1': [6, 6.1, 6.2, 6.3], # Industrial robots for handling adoption adoption

    'AR3 m09q1': [7, 7.1, 7.2, 7.3], # Mobile industrial robots adoption

    'AR4 m09r1': [8, 8.1, 8.2, 8.3], }# Collaborating robots adoption

df = pd.DataFrame(data)

# -99 missing removal

df = df[df.PLM != -99]

df = df[df.MES != -99]

fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10, 5))

ax[0].hist(df['PLM'], bins=3, edgecolor='black')

ax[0].set_title('PLM Distribution')

ax[0].set_xlabel('PLM Value')

ax[0].set_ylabel('Frequency')

ax[1].hist(df['MES'], bins=3, edgecolor='black')

ax[1].set_title('MES Distribution')

ax[1].set_xlabel('MES Value')

ax[1].set_ylabel('Frequency')

plt.tight_layout()

plt.show()

# Regression

sns.regplot(x='PLM', y='MES', data=df, logistic=True, ci=None)  # logistic regression as data is binary

plt.title('Regression Plot between PLM and MES')
```

Figure A.4: Scatter Plot with Trend Line for Model Support Against 'Outcome' Categories

```
data = pd.DataFrame({ # Tabulated logistic training results
    'Outcome': ['FF', 'TF', 'Accuracy', 'Macro Avg', 'Weighted Avg'],
    'Precision': [1.00, 0.88, None, 0.94, 0.92],
    'Recall': [0.71, 1.00, None, 0.86, 0.90],
    'F1-Score': [0.83, 0.93, 0.90, 0.88, 0.90],
    'Support': [7, 14, 21, 21, 21] })
palette = {"FF": "#1f77b4", "TF": "#ff7f0e"}
plt.figure(figsize=(20, 6))
# Plot 1 for Precision, Recall, and F1-Score for FF and TF
plt.subplot(1, 2, 1)  # 1 row, 2 columns, first subplot
bar_data = data[:2].melt(id_vars='Outcome', value_vars=['Precision', 'Recall', 'F1-Score'])
bar_plot = sns.barplot(x='variable', y='value', hue='Outcome', data=bar_data, palette=palette)
plt.ylim(0, 1.1)
plt.title('Precision, Recall, and F1-Score by Outcome')
plt.ylabel('Score')
plt.xlabel('Metric')
plt.legend(title='Outcome')
for container in bar_plot.containers:
    bar_plot.bar_label(container, fmt='%.2f', padding=3)
# Plot 2 for F1-Score for Accuracy, Macro Avg, and Weighted Avg
plt.subplot(1, 2, 2)  # 1 row, 2 columns, second subplot
f1_data = data[2:].melt(id_vars='Outcome', value_vars=['F1-Score'])
f1_plot = sns.barplot(x='Outcome', y='value', data=f1_data)
plt.ylim(0, 1.1)
plt.title('F1-Score for Accuracy, Macro Avg, and Weighted Avg')
plt.ylabel('F1-Score')
plt.xlabel('Metric')
for container in f1_plot.containers:
    f1_plot.bar_label(container, fmt='%.2f')
plt.tight_layout()
```

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An exploratory analysis of supply chain contracts on efficiency, simulation, and data analytics augmentation technologies.
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II

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 between advanced manufacturing technologies and 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 (SDA) 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, Data-Analysis, 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).

This research is comprised of two parts. The first part was conducted through a Scopus search. The data plotted in Figure 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 Figure 1. Topics of each topic range of interest are followed, substituting the {topic} with each additional with a more detailed search term. The Figure 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.).

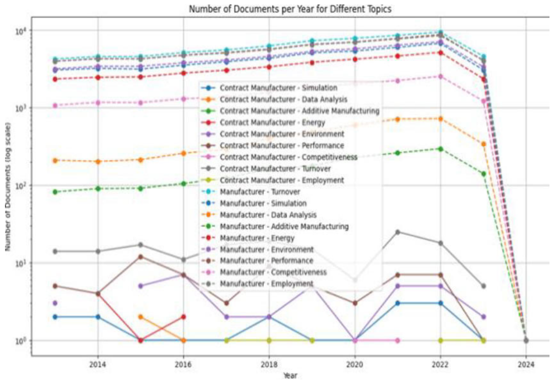

Figure 1: Mostly positive trends in the long term in document counts by topic and year for contract manufacturers and manufacturers, plotted on a logarithmic scale. Each line represents the documents with solid lines for "contract manufacturing" and dashed lines for "manufacturer." The topics include "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.).

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 (1).

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

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:

1.) What is the influence of a company's descriptive[1] parameters on the adoption of advanced manufacturing[4] techniques from the SCC[2] perspective?
2.) How does a firm's HR[3] background affect the adoption of advanced manufacturing[3] techniques[4] from the SCC[2] 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*

III. 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 multi-method 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 interact and predict the relationships between variables.

IV. Instruments used

The research tool was constructed based on the EMS22 model and implemented in Finland to foster corporate-level 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, m03a4-m03a5), 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.

V. 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 1 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 in-depth 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 1: Descriptive Statistics (EMS 2022 results)

	MIN	MAX	M	MED	MOD	STD	SKEW	KURT	SUM	VALID
AT21	0	339	26.219	6	1	52.445	3.767	17.641	2071.329	79
AT19	0	326	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 2: Construct correlations (EMS 2022 results)

	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	I																							
AT19	.991 ****	I																						
NE21	.818 ****	.807 ****	I																					
NE19	.822 ****	.831 ****	.983 ****	l																				
MCU21	.243 *	.267 **	.131	.123	I																			
MCU19 .	.245 *	.244 *	.209	.195	.829 ***	I																		
ROS	.233 **	.221 *	.221 *	.203 *	.300 **	.241 *	I																	
IEM	.398 ***	.404 ***	.265 **	.307 **	.002	-.021	.214 *	I																
AP	-.338 ***	-.283 **	-.274 " *	-.297 **	-.163	-.378 ***	-.112	-.072	I															
EYF	.149	.147	.270 **	.317 ***	.146	.212	.129	.548 ****	-.407 ***	I														
MFR	-.122	-.135	-.147	-.149	.217 *	.077	.184	.097	-.093	.175	I													
SPR	-.077	-.069	.006	.013	-.083	-.008	-.276 **	-.106	.203 *	-.226 **	-.343 ****	I												
CM	-.038	-.051	-.048	-41	.102	.194	.031	-.09	-.153	.101	-.354 ****	-0.166 *	I											
SCC	-.208 *	-.22*	-162	-151	.202	.231 *	-.058	-.095	-.02	.034	.268 ***	.435 ****	.425 ****	I										
GUC	-.044	-.001	-.036	-.016	-.319 **	-.393 ***	-.250 **	.043	.491 ****	-.237 **	-238 ***	.391 ****	-.217 "	-.06	I									
TSW	-.047	-.066	.15	0	.192	.162	.083	-.065	-.207 *	-117	.172º	-.127	-.004	.036	-.359 ****	I								
TF	.056	.065	-.01	.001	.183	.244 *	.014	-.002	-.149	.125	-.066	-.122	.138	-.04	-.411 ****	-273 ***	I							
SUW	0	-.044	.11	-.012	.023	.094	.235 **	.013	-.324 ***	.293 ***	.212 **	-.220 **	.087	.069	-.429 ***	-.201 **	-.293 ***	I						
TCT	.285 **	.260 **	.221 **	.215*	.022	.018	.201*	.012	-.064	.108	-103	-.057	.246 ***	.077	-.119	-.112	-.056	.163 *	l					
HR	.271 " *	.236 **	.217 **	.206 *	.1	.112	.257 **	-.005	-.192	.145	-.024	-.148	.275 ***	.091	-.350 ****	.066	-.035	.265 ***	.966 ****	l				
ET	.295 ***	.306 ***	.298 ***	.311 ***	.042	-.075	.062	.227 *	-.134	.161	-.038	-.137	.123	-.05	-.214 **	-.036	-.037	.311 ***	.154 *	.197 **	I			
SDA	.173	.195 *	.330 ***	.340 ***	.043	.011	-.009	.054	-.042	.145	-.008	0	.062	.047	.079	-.055	-.168 *	.107	.167 *	.14	.433 ***	l		
PMC5	.224 **	.225 **	.344 ***	.376 ***	.21 *	.053	.284 **	.213 *	-.189	.540 *****	.153 *	-.249 ***	.056	-.04	-.205 **	.004	.003	.226 **	.106	.15	.254 ***	.211 **	I	
PMC6	.363 ****	.388 ****	.475 ****	.518 ****	.206	.11	.103	-.074	-.23	.153	.044	.024	-113	-.04	-.085	.055	.138	-.099	.044	.06	.163 *	.221 **	.393 ****	l
	AT21	AT19	NE21	NE19	MCU21	MCU19	ROS	IEM	AP	EYF	MFR	SPR	CM	SCC	GUC	TSW	TF	SUW	TCT	HR	ET	SDA	PMC5	PMC6

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

B. *Study Methodology: Correlation Modeling*

Pearson's correlation (R) is employed to assess the correlation between DCES and KETs parameters of interest (Table 2). 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 2. 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.

VI. 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.

VII. 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, succesful 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.

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III

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.**

***Index Terms*— 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 figure 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 "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).

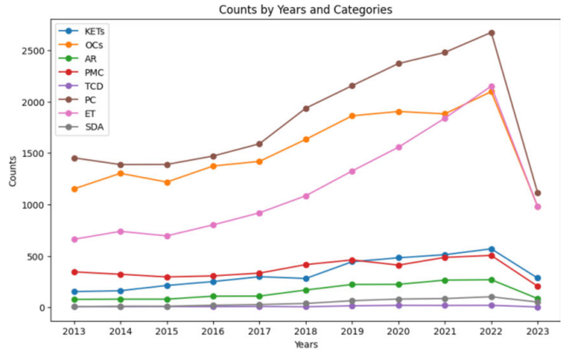

Fig.1. Scopus documents related to manufacturing in the last 10 years.

As depicted in Figure 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 (Abualooush 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 (as 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 2022b). 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).

III. 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, 48). 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.

IV. 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.	I	
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.	I

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

V. 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.

A. 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.).

B. 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.

A. 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

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).

B. 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.

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	.314	.28 **	1

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

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).

VI. 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 toptier 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

Author correspondence Janne Heilala implementation of EMS22 research with Jussi Kantola. This chapter's analysis view share correspondence and co-authorships of Antti Salminen, and Wallace Moreira Bessa.

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Relocation activities for the development of employment and competitiveness situations.
Industrial Engineering and Operations Management

IV

Relocation activities for the development of competitiveness and employment situations

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Abstract.

The recent version of the European Manufacturing Survey (EMS) was done in Finland by asking companies' CEOs or cognizant personnel (n=123) to respond. This study aims to report the results of the following Development of Competitiveness and Employment Situations (DCES) covering Annual Turnover (AT), Number of Employees (NE), Manufacturing Capacity Utilization (MCU), Return on Sales (ROS) concerning corporations' operations: Relocation Activities (RAs) converging to Offshoring Manufacturing Performance (OMP), Backshoring Foreign Manufacturing (BFM); Offshoring R&D (ORD); and Backshoring Foreign R&D (BFRD). The defined research question, "How do the DCES and RAs relate?" was answered by seeking influences directly for AT and NE corresponding to all RAs positively except negative BFRD. Large corporations can be said OMP, but the sample also has smaller companies those that BFM. The reason for BFM could be the decreased ROS with a statistically significant negative impact during the COVID-19 fiscal year 2021.

Keywords: Industry 4.0; Global Supply Chain Management; Manufacturing Competitiveness; Organizational Concepts;

1 Introduction

The first results of the European Manufacturing Survey (EMS) Finland discuss research on key enabling technologies for manufacturing. Heilala (2022ab) found that manufacturing technologies' parent variables: production control was accurate, automation and robotics were not even near, efficiency technologies were very far away, and simulation, data analyses, and additive manufacturing were on the same page, as manufacturing capacity utilization or returns on sales were not evenly distributed among the technologies variables in use. Thus, the study found the association with returns and explained why technology integration benefits what organization concepts are fulfilled (Heilala 2022abc). The organization concepts were considered to assess current organizational innovations in manufacturing technologies by structuring the operations in optimized rotation to ensure that the technologies used are efficient for high manufacturing capacity and return on sales contribution. To this end, a fascinating question arises; "Where do companies use their technologies and employees to grow their profits?" competitiveness is built by locating in an optimal business location. For the large organizational differences, the respondees' operating environment is an important consideration in understanding the development of employment and competitiveness situations more broadly. The inflationary and deflationary weaknesses or advantages explain how some corporations had negative and very positive financial indicators for operations and why the organization concepts and manufacturing technologies' beneficial use varies on a large scale largely. Could it be that the measure included corporations with multi-site foreign operations?

This paper aims to find out the Relocation Activities (RAs) practices of the companies that responded to the survey operating in the Finnish Servicing Manufacturing Market Environment (FSMME) for the first time concerning the development of employment and competitiveness Situations (DCES). The data were acquired using the European Manufacturing Survey (EMS), and generally, from the responses, CEOs and equivalent leaders gathered the most unity in their organizations from the department heads. Past research in the EMS consortium has tied most EU member states' RAs to the free-access publication level, where the study findings have helped newcomers and existing players to position and change their intuitional strategies based on open research guidelines (Kinkel & Maloca 2009; Dachs et al. 2012; Dachs & Kinkel 2013; Kinkel 2014; Dachs & Zanker 2015; Dachs et al. 2019).

This report follows the method used in EMS, multi-method, quantitative research. It has a reliably broad dissemination method, as the research was disseminated through multiple channels to reach as many interested CEOs as reachable. The collection, pruning, and splitting of the dataset into parts are explained concerning the entirety of this study. The analysis method was to fit regression to see the dummy variables in connection with the operations used in the companies in a very cross-sectional manner. The data analysis convergently investigates the mutual relationships between all thematic subsets on relocation operations, relying on the first given descriptive variables that show a very representative spectrum, which is critical for a few corporations. Introductory to the foreign operations anatomy travel destinations and reasons will be given by the respondees practices, which could have been more evenly distributed. For the respondees' rareness, the image is used in all companies for consideration, whether situations require changes within the scale of the likelihood for larger turnover and number of employees, and whether external factors selectively affecting different companies' operations are unequally operating.

The unevenly distributed negative random factors justify offshoring research and development to the more technologically advantaged locations among corporations to gain leverage of the deflationary levers speculatively or to increase the global market share. For instance, offshoring foreign manufacturing for large corporations expects increased manufacturing capacity utilization and thus return of sales while requiring smaller corporations to backshore foreign manufacturing because the negative return on sales can occur as rising prices in less deflationary advantaged countries, which have been reported during the COVID-19 fiscal year 2021. For over some time, history shows that years before now, climate change has been a fatal factor in generating losses, resulting in vulnerabilities in value chains, which will be emphasized in the future (Raza et al. 2021). It is claimed that the different quartiles of the entrepreneur series' lowest tail can suffer losses. It is explicitly associated with digitalization laggards (OECD 2021, 6-7) and easily measurable costs, particularly labor (adapted to Heilala 2022a; Dachs et al. 2019). If labor costs suddenly increase, it creates a challenge to maintain the company's operations as a counterweight to serving the market efficiently. Urgent backshoring of foreign research and development needs is likely the reason for raised cost structures that surpass the return on sales and are also expected negatively, walking hand in hand with annual turnover and number of employees, expecting smaller corporations to take damage in foreign markets and transition production back to headquarters.

2. Research problematization and hypotheses

Machine learning-governed supervised learning can resolve observations in the spectral dimension with astonishing precision, offering several ways of examining the phenomenon. It involves interdisciplined, systemic action conducive to cross-sectional validity over the EMS database content. The RQs treat subconcepts under top-level research questions. A research question identifies relocation activities that can serve to assist decision-makers within corporations and other institutions in determining the level, association, and context of the development of employment and competitiveness situations in the Finnish manufacturing market environment. Before integrating the research questions, the following sub-research questions were defined to cover the study objectives:

1. How did corporations’ offshoring manufacturing performance operations predict the study sample respondees by annual turnover measures, number of employees amount, factories manufacturing capacity utilization, and return on the sales side?
2. How does sample respondee corporations’ backshoring foreign manufacturing plot change in the site expect the study by annual turnover measures, number of employees amount, factories manufacturing capacity utilization, and return on the sales side?
3. How does corporations’ offshoring R&D use expect the entire purview of the study sample respondees by annual turnover measures, number of employees amount, factories manufacturing capacity utilization, and return on the sales side?
4. How do corporations backshoring foreign R&D use expect sample respondees the entire span by annual turnover measures, number of employees amount, factories manufacturing capacity utilization, and return on the sales side?

What was the most efficient way for companies to decentralize their operations to achieve the highest levels of competitiveness? Hypotheses mapping was conducted based on the EMS database findings to address the research questions. Through the recursive modeling of sub-research questions, 32 hypotheses were established regarding latent entities according to the cross-sectional approach.

Table 4: Construct correlations hypotheses

	AT	NE	MCU	ROS	OMP	BFM	ORD	BFRD
AT	1							
NE	n.s./n.c.	1						
MCU	n.s./n.c.	n.s./n.c.	1					
ROS	n.s./n.c.	n.s./n.c.	n.s./n.c.	1				

OMP	n.s./n.c.	n.s./n.c.	n.s./n.c.	n.s./n.c.	1			
BFM	n.s./n.c.	n.s./n.c.	n.s./n.c.	n.s./n.c.	n.s./n.c.	1		
ORD	n.s./n.c.	n.s./n.c.	n.s./n.c.	n.s./n.c.	n.s./n.c.	n.s./n.c.	1	
BFRD	n.s./n.c.	n.s./n.c.	n.s./n.c.	n.s./n.c.	n.s./n.c.	n.s./n.c.	n.s./n.c.	1

Note hypothesized variables axioms: not having significant relation/not correlating (n.s./n.c.), while 1 indicates to satisfy.

3. Research methodology

3.1 Research set up

Finland's first EMS results compiled. The research was distributed virtually but also in printable form for large corporation divisions' support to be filled by pen and responded to by departments from or on behalf of CEOs or other steering group members (Heilala 2022bc.). The sources are input from the web portal news and e-mail newsletter.

3.2 Analysis protocol

The EMS database was analyzed with mixed methods to understand intrinsically quantifiable metrics from the database and its variables indices collected and definable. The variable tensors were measurable from the logged sessions the respondees mentioned above gave in the Webropol system. (Heilala 2022bc.) the analysis method from this dataset is used to understand how the manufacturers are positioned in the Finnish servicing manufacturing market environment, likely also in foreign operations. The most laborious part was the dataset pruning and selecting the responses for the information acquisition forms given responses. Explanatory variables analysis was suggested to be implemented by probing interactions on multilevel regression (Dachs & Kinkel 2013), which is taken into account in developing the measurement depths in Finnish and European scales for variable computational interaction situations. The employment and competitiveness of the industry are susceptible to marginalized results. Even in a single study or series of studies of EMS, quantitative data is collected, analyzed, and mixed with qualitative information, which directly brings the respondees' voices in a computationally analyzable form to be able to simulate the researcher's philosophical questions. According to this approach, quantitative and qualitative approaches can be combined more effectively than either approach alone to understand research problems better. (adapted to Creswell & Plano 2007.)

The selected variables are logical in the cross-sectional investigation of companies, whereby best and worst mean ends are inferential to the effects of one predictor on another. Relocating businesses establishes conditional relation towards growth, best measured by annual turnover and the number of employees. The probing interaction whether the value of offshoring or backshoring would be omitted from specific companies working in domestic markets. The movement of operations can expect specific companies and characteristics to explain the responses that explain the behavior as the dependent variable, to which the range of variables can provide explanations e.g., for operations. When the whole spectrum is considered, the other measurements can provide existing alternatives, which can be seen as unsatisfying for some researchers. This is why this research protocol does not standardize the measurement relations but focuses on preparing regression. Explanatory variables are used to analyze the data for regression. For the analysis of connections, the correlation coefficients were used instead because, for embedded correlation modeling, the model is not interested in variable dependencies or directions, i.e., they have been omitted. Since the sum of variables cannot be multicollinear to be processable, there should not be a strong correlation among variables, which is supportive of choosing meaningful variables for regression. Because variables should not have neutral correlations for integrative variables, these can be omitted. The variables can only be used if a linear result is obtained. Regression analyses are generally believed to be reliable when at least 40 observations per variable exist. A sample-specific steering analysis can only be performed since the clustering sample size (n = 123) covers only this study's sample. Ultimately, the regression test can be used to determine confidence intervals. We suggest that the European Commission supports Horizon Europe (HE) funding by following the regression analysis results and deducing the EMS characteristics' outcomes in, for example, project organization forming. (Heilala 2022bc.) It is also possible to use correlation coefficients as predictors since they also serve as explanatory rates, but the continuous variables have no position on the directions.

4. Data Analysis

4.1 Descriptives

The descriptives provide information about the variables' measures. Minimum to maximum indicates respondents' response range: Annual Turnover (AT) values (million €); Number of Employees (NE) displays employees count; Manufacturing Capacity Utilization (MCU) indicates the usage of the main operations; Return of Sales (ROS) value scale indicates (from 1 to 5: negative, 0-2%, >2-5%, >5-10%, and >10%) before tax; and Offshoring Manufacturing Performance (OMP); Backshoring Foreign Manufacturing (BFM); Offshoring R&D (ORD); and Backshoring Foreign R&D (BFRD) reveal if the company has been in transient mode (binary). (adapted to Heilala 2022a; 2022b; 2022c.) The relations based on embedded correlation modeling are about the sum variables' relation to each other, i.e., the sum of the variables for each dimension of the European Manufacturing Survey has been calculated and then divided by the number of total variables, cf. Table 2.

Table 2: Construct descriptives

	MIN	MAX	M	MED	MOD	STD	SKEW	KURT	SUM	VALID
AT	0	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	100	66.67	75	80	28.975	-1.227	0.664	4267	64
ROS	1	5	3.42	4	5	1.567	-0.509	-1.29	267	78
OMP	0	1	0.12	0	0	0.329	2.354	3.629	10	82
ORD	0	1	0.09	0	0	0.281	3.023	7.319	7	82
BFM	0	1	0.04	0	0	0.19	4.996	23.54	3	81
BFRD	0	1	0.01	0	0	0.111	9	81	1	81

The mean of 26.219 million euros and the standard deviation of 52.445 million euros are calculated for a sample of zero to 339 million euros AT. The sample distribution appears to have a positive skewness, as a few participants fall at the most positive end of the tail. A platykurtic model's distribution is negatively skewed for MCU and ROS. According to leptokurtic peak performance for AT, the sample included a few large and some smaller companies. Based on the fact that the largest provider has 600 employees, while the smallest provider has three, NE has similar curve characteristics to AT, following its skew and kurtosis. ROS is the last, perhaps most captivating, indicator of competitiveness (M = 1, 2 to 5). (Heilala 2022bc.) a grand mean of 3.42 implies that, on average, companies have positive returns. For the operations side, it is highly likely that in the light of statistics, very few corporations have faced offshoring and backshoring activities because all distributions are skewed positively to the binary zero, while few players face challenging situations. 12 % of the corporation offshored manufacturing, 8.5 % offshored R&D operations, 4% backshore manufacturing, and 1% backshore R&D. After all, there are no generalizable results foreseen for the sample operations here in terms of transfer, except that the majority do not transfer. However, it is important to look at the learning ability factors and what kind of companies usually perform this activity, which we delve deeper into next.

4.2 Model Correlations

It is possible to determine the correlation between the development of employment and competitiveness situations and relocation activities model parameters of interest using Pearson's correlation (R), which describes how two variables change together over time. In non-linear correlations, variation is represented from -1 to 1 in the R-coefficient, determining the intensity and direction of linear correlations. The positive value shows that the variables are perfectly correlated, the negative value indicates an inverse correlation, and when the value is near 0, the variables do not match. Barlett's sphericity test indicates a barely satisfactory score for the model because the unsaturation is so high. The determinant (d=.051) and Kaiser-Meyer-Olkin values for the individual investigation of the relocation activities on development of competitiveness and employement situations are (0.52 to 0.56). The model yielded values in Table 1. (adapted to Heilala 2022bc.)

The research questions share different weaknesses than (Heilala 2022b). How the results' reader herein should position the scale depends on the viewpoint on the study design for assessing the results. Whether to take responses seriously together makes a barely satisfactory model, but on the other hand, reducing respondees could have led to gaining a perfectly validatable model. The first one requires a curious angle of entry on scale effects because there are large corporations among smaller ones, and the large corporations are not necessarily revealing or have information for relocation activities available. At the same time, the model's hard quantitative grounding explores the very few factor outcomes by the CEOs' responses that were yielded in EMS and rotated through regression and resulted in relocation activities outcome space shown in Table 2. (to manufacturing key enabling technologies and organizational concepts used and adapted from Heilala 2022abc.) The tool proves to have low internal consistency in correlative means. However, its performance measure does not reject its factorability, and it can always be done in pairs if the model weaknesses reproduce challenges further.

Table 4: Construct correlations

	AT	NE	MCU	ROS	OMP	BFM	ORD	BFRD
AT	1							
NE	0.905****	1						
MCU	0.244**	0.18*	1					
ROS	0.243**	0.179*	0.298**	1				
OMP	0.228**	0.283**	0.046	0.042	1			
BFM	0.085	0.168*	0.037	-0.171*	-0.075	1		
ORD	0.135	0.257**	-0.049	0.091	0.357***	-0.06	1	
BFRD	-0.078	-0.083	-0.013	-0.21	0.391***	-0.029	0.487****	1

Note: results are not having significant relation/not correlating (n.s./n.c.), ****p<0.001, ***p<0.01, **p<0.05 and *p<0.1

Table 4 shows the DCES having the same connections as in (Heilala 2022a; 2022b). The model had a relatively small number of players on OMP or within other actions. In theory, however small the signals caused by the movements are, they are essential in convergent validity since corporations seek different growth-related achievements when expanding to international markets. The table findings indicate that the OMP is relatively highly predictable by the AT. It is because large corporations are needed to move from domestic markets to foreign in terms of possibly supplying the manufacturing feed on the customer locations beneficially, which requires further investigation and clarification in forthcoming Figure 1.

On the contrary, BFM is the majority. However, a proportionally slightly lower number of players are expected to impact repatriating operations, as can also be seen in Figure 1. MCU perspective without clear statistical significance to validate results, and the connection remained relatively low. However, the directions are interesting because statistical dispersion and randomness are not random. However, intentional retreating for players' businesses, appearing as statistical anomalies, are significant results and should be taken seriously. It calls for a closer look at what perspectives were retracted. It would seem that OMP and ORD walk hand in hand, while BFM and BFRD do not seem to be in contact with each other. It also showed meaningful links to ORD, confirming that the players keep operations alive by repatriating old operations and connecting to new areas simultaneously, which needs closer examination in Figure 1.

Figure 1 map coding and legends indicate that the OMP has focused on the Baltics (Estonia, Lithuania, Latvia), Central Europe (Poland), Southwestern Europe (Portugal), East Asia (Japan and China), South Asia (India), The US, and Canada. The reason is that the operation costs, i.e., price and certainty, are opportunist for employee relocation from the opportunistic beginning of the core company. In some cases, delivery time is much quicker. Secondly, BFM expects respondents to relocate to the headquarters of their parent company. Thirdly, for multisite-based operations, ORD is popular for travel destinations in North-western Europe (Belgium), Central Europe (Germany and Poland), Baltics (Estonia), South Asia (India), Nordic countries (Norway and Sweden), southwestern Europe (Spain). Due to the availability of labor or competencies at a reasonable cost, the owner of an unidentified corporation contends that BFRD from India is feasible due to the lack of functional performance available (based on EMS22 open-ended data Heilala et al. 2022.)

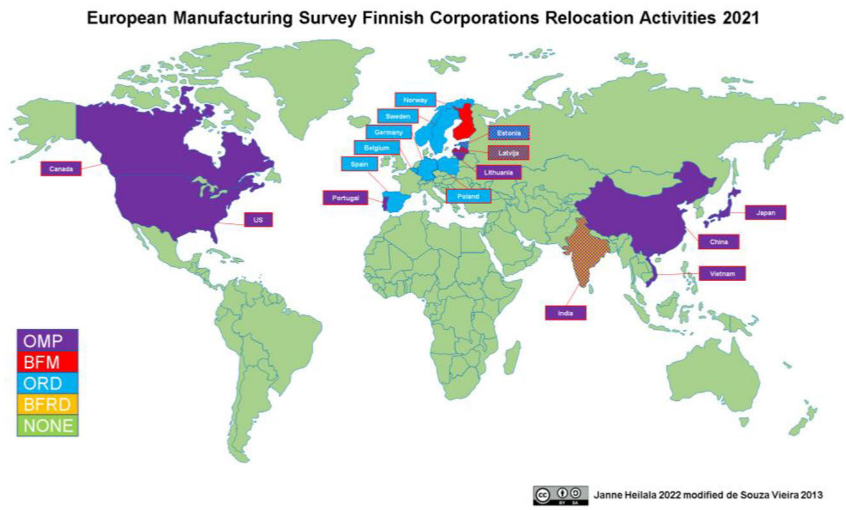

Figure 1: Certain Travel Destinations for Offshoring Manufacturing Performance (OMP); Backshoring Foreign Manufacturing (BFM); Offshoring R&D (ORD); and Backshoring Foreign R&D (BFRD) connections (Heilala et al. 2022)

5. Conclusions

To answer the first research question, based on the data from the research, companies' production outsourcing activities predicted the extent of total employment and competitiveness development outsourcing activities in terms of annual turnover, such that medium-sized companies with turnover typically transfer production. At the same time, the number of employees refers to reasonably large companies. Concerning the number of employees, the reason for moving operations abroad is primarily cheap labor (e.g., China) - but the printouts are very cheesy from their consistency, as it is only visible in some companies' manufacturing capacity utilization and corresponding returns. Furthermore, this shows that only some things can be successfully carried out in domestic markets, i.e., reasonably weak Finnish entrepreneurs offshore their operations abroad because it may be more profitable in the light of the research results but resembles a risk-taking. A small signal indicates that the production runs fluently and better in foreign operations. When the market is pulling either ostensively or performatively led, it appears as positive returns, so the given recommendation from the sample is to move operations overseas while keeping the core business innovation in Finland.

To address the second research question and answer the prospects of companies' backshoring foreign manufacturing operations: whereby companies operating in Finland have recorded a response of forced or volunteering (not directly measured the cause- or reason) to transfer their business back to domestic trade has been processed. At this point, the changes to be announced are expected in the scope of the relocation activities operations for the development of employment and competitiveness situations perspective in terms of annual turnover positively but not equal statistically. However, in terms of the number of employees, there seems to be regularity, meaning that, by and large, companies of the same size belong to a cluster number of employees with a fairly strong connection. This cluster is also affected by a small rising production capacity utilization rate and negative return sales, statistically significantly showing the reason to move back because production costs have increased in the country of production.

In order to answer the third research question, we discuss the expected total employment of R&D offshoring and the extent of transfer measures intended to develop competitiveness in terms of annual turnover, which is a fairly positive relationship without equality, i.e., companies have weaker and stronger actors that do not outsource R&D. However. It can appear as an ideal model for companies that do not do this. The motivating result is that if the company offshores R&D operations, the company has a lot to do with the number of employees, so it is worth outsourcing research, but with caution. The justifying factor may be that the company wants to increase its small production capacity.

Finally, let us move on to the strict place exchange fence, the fourth research question, to answer how companies' use of backshoring foreign R&D expects the full extent of relocation activities intended to develop employment and competitiveness in annual turnover. It gave negative and statistically insignificant results, but it is a critical topic of conversation in practice. This means that some small companies are bringing their businesses back to Finland, meaning that technology is being patriated. However, it also speaks of challenges because the number of employees is seen expecting sample's small companies. The negative manufacturing capacity utilization appears to be a small cause- or reason for this, whereby the relation to returns is also strongly negative due to lacking sales. None of these is statistically a good thing. However, on the contrary, the research results show that small entrepreneurs bring their R&D functions back because the offshored performance fails to sustain at expected levels.

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Advanced engineering management based on intersectional R&D challenges on education: a case study for product classifications on shoring trends.
Human Factors in Design, Engineering, and Computing

V

Advanced engineering management based on intersectional R&D challenges on education: a case study for product classifications on shoring trends

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Abstract

This study tethers how leading Finnish manufacturers and R&D departments approach sustainable global manufacturing practices. Drawing insights from the comprehensive 2022 European Manufacturing Survey (EMS), the analysis explores how principles of sustainability manifest in mechanical engineering, focusing on aerospace design as an exemplar. Empirical findings reveal corporate relocation trends, highlighting preferences for offshoring manufacturing versus R&D operations to strategic geographic regions. The research examines offshoring decisions through the lens of additive manufacturing, energy systems, and organizational dynamics captured in the EMS data. Explorative correlation analysis of EMS variables provides a quantitative baseline, complemented by contextual insights from academic literature on sustainable business models and training innovation. Geographic patterns show proximity advantages for nearshoring to Nordic innovation clusters, while talent incentives pull certain activities towards South Asia. A case study showcases integrated product design aligning with international sustainability benchmarks. While exploratory, the multi-faceted analysis offers original perspectives on the complex factors influencing modern corporations' globalization strategies. The synthesis of empirical observations, conceptual literature, and an exemplar sustainable product line provides a novel framework for navigating offshoring decisions. The discussion examines pathways to fortify training and help manufacturers balance global market access with robust domestic engineering ecosystems.

Introduction

Exploring the frontiers [1] of sustainable manufacturing invites us to look to the cosmos itself. Just as groundbreaking discoveries in understanding the accelerating expansion of the universe have transformed astrophysics, innovations in manufacturing exchange mechanics hold promise for a new era in industrial sustainability. This study examines how leading Finnish manufacturers and R&D operations are aligning with these shifts, drawing insights from the 2022 European Manufacturing Survey (EMS).

Using aerospace engineering as a conceptual springboard, we bridge the theoretical and the applied. Parallels emerge between mechanical engineering design and principles of spaceflight navigation. Much as Newton unpacked the forces governing the fall of an apple, this research delves into the complex factors shaping modern offshoring decisions. The EMS offers a window into Finnish manufacturing priorities, signaling how product development strategies integrate with evolving international trade frameworks like UN classification systems. Europe's progressive approach also provides guidance on how to translate sustainability from theory into practice.

As the intricate algorithm of the future of manufacturing comes into focus, Finnish industry leaders are demonstrating how to leverage innovation to drive this transformation. The confluence of scientific rigor, human-centric design and environmental sustainability points toward a new paradigm for engineering education and industry collaboration. By exploring key issues like additive manufacturing through an interdisciplinary lens, this study seeks to highlight how Finland's manufacturing sector can continue exploring sustainable frontiers. [1]

Research questions and Empirical research

To cover the objectives of the study, the following research questions (RQs) were defined by selecting a case EMS:

To propel our investigation of Finnish manufacturers' approaches to sustainable global operations [1], we defined three central research questions:

- How are offshoring decisions for manufacturing and research and development guided by principles of sustainability development?

Earlier research has underscored the relevance of environmental considerations in offshore production, particularly example regarding energy efficiency infrastructure. This prompts an examination of how relocation choices account for sustainability factors on optimization.

- What protocols can guide integrated domestic and international operations to uphold sustainable priorities?

Standardized frameworks like ISO certifications provide reference points for sustainable business practices. This suggests a need to evaluate how corporations reconcile domestic and offshore protocols before rabbit-holes, for mapping the need of education technologies.

- How do quality management principles manifest in determinants of sustainable enterprise operations for aerospace design engineering?

Establishing consistency across supply chains requires harmonizing environmental and quality standards. The research assesses how manufacturers embed sustainability into design of quality frameworks. While there to capture and handle data, nearside is considered.

By approaching offshoring decisions through these multifaceted research questions, our analysis aims to elucidate the dynamics enabling manufacturers to integrate sustainability initiatives across local and global operations. The literature suggests certification models could support reconciling inter/national variances, though small firms face greater obstacles in implementation. This investigation seeks to provide a greater track on navigating these complexities.

EMPIRICAL LOCALIZATION

Finnish EMS dialectically offered manufacturing and R&D depthness: companies signifying offshoring and aligning into backshoring. The analysis part numbers are first withdrawn for a representative sample, and results are elaborated with case extensions. The method introduced as of advanced structures correlation modeling. [1]

Descriptives and interconnections

The respective sample characteristics withdrawn from the study were represented, minimum, maximum, mean, median, mode, standard deviation, skewness, kurtosis, sum, and validity of the sample responders on given measure indices [1, table 1 p. 233]. Declension focuses on the correlation between variables emphasized by offshoring or backshoring manufacturing. Respectively, the connection structure was presented. The variables in the tables take the following arguments based on abbreviations. By breaking this down, the study measure includes AT21 and AT19, representing the Annual Turnover for 2021 and 2019, respectively. NE21 and NE19 denote the Number of Employees for those same years. MCU21 and MCU19 refer to Manufacturing Capacity Utilization for 2021 and 2019. Other metrics include ROS (Return on Sales), OMP (Offshoring Manufacturing Performance), and ORD (Offshoring R&D). BFM indicates Backshoring Foreign Manufacturing. At the same time, BRD is for backshoring R&D. ET stands for Efficiency Technologies, and SDA (Simulation, Data Analysis, and Additive Manufacturing). The study also introduces two Energy and Efficiency Management Systems variants labeled PMC5 and PMC6. Breaking this down in [1, table 2 p. 234] in monodirectional declension.

The sample characteristics taken from the study were represented by minimum, maximum, mean, median, mode, standard deviation, skewness, kurtosis, sum, and validity of the sample responders on the given measure indices [1, table 1 p. 233]. The focus is on the correlation between variables emphasized by offshoring or backshoring manufacturing. The connection structure was presented respectively. The variables in the tables take the following arguments based on full terms. The study measure includes the annual turnover for 2021 and annual turnover for 2019. Number of employees for 2021 and number of employees for 2019 are also included. Manufacturing capacity utilization for 2021 and manufacturing capacity utilization for 2019 refer to capacity. Other metrics were return on sales, offshoring manufacturing performance, and offshoring research and development. Backshoring foreign manufacturing indicates bringing manufacturing back. Backshoring research and development refers to bringing research and development back. Efficiency technologies and simulation, data analysis, and additive manufacturing were also included. The study also introduces two energy and efficiency management systems variants labeled process and manufacturing control system 5 and process and manufacturing control system 6. Breaking this down in [1, table 2 p. 233] in monodirectional declension.

Off- and backshoring manufacturing or R&D

The decision to offshore manufacturing outside of Finland comes with considerations. While there is not a stringent requirement for adopting efficiency technologies, energy certifications, or environmental management systems, there is an undeniable emphasis on data analysis, simulation, and prototyping, especially using additive manufacturing. Simultaneously, the firm is expected to maintain a central hub or headquarters for research and development. Notably, from the backshoring R&D perspective, smaller companies often do not need more pressure to obtain these certifications. [1]

Regarding smaller design offices’ growth expectations, offshoring manufacturing enables exploration of the flexibility offered. On the contrary, established factories, which have been operational longer, often have a larger workforce and have typically adopted a certified energy management system with a stable operational footprint in domestic regions, as [1] noted.

An intriguing business perspective is the financial viability of outsourcing activities to nations with a political and financial incentive for energy management and environmental conservation. According to recent research, this approach is financially sustainable, especially in countries where environmental considerations were rewarded [1]. However, the taxation system often favors larger corporations, leaving smaller enterprises bereft of these benefits. Countries in Central Europe, Southwestern Europe, East and South Asia, and North America were favorable for offshoring manufacturing performance.

However, regarding research and development offshoring, Northwestern and Central Europe, the Baltics, South Asia, and the Nordic countries were preferred destinations packed with possibilities. From a logistical standpoint in nearshoring, the most sustainable relocation options for manufacturing for Finnish companies were the Nordic countries, the Baltics, and Central Europe.

Classifying international trading

Human systems integration compatibility between industrial systems from legislative and economic perspectives is presented in former studies. Representation is the so-called Nomenclature Générale. Domain's integration into economic activities is selectively represented in the global schematic drawing [1, p. 236). They integratively illustrate the interplay of human and industrial systems within legislative and economic contexts. The Nomenclature Générale exemplifies this through various products, emphasizing the significance of responsibility. Quality validation, crucial for facilities such as productized universities, complements the need for product development certification in the digital era. Offshoring, with its evolving dynamics, underscores the development trajectory. The UN's ISIC (Int Classification of All Economic Activities) regional classifications emphasize understanding economic activities through global and local lenses. Discerning these by country and specific indicators for efficacious industry interpretation has implications for regional development—integrated data access, particularly in inclusive supply chain engineering [2]. The progressive approach is exemplified by Eurostat standards and mirrored by the UN's interpretation. The UN's CPC (Committee for Programme and Coordination/Central Product Classification) certified production classification (such as PRODCOM) should be a developing product taxonomy covering everything from fundamental to state-of-the-art processes. Merging classifications underlines the foreign trade statistical framework synergizing with ISIC's global trade data. These systems reveal details about the elaboration of connections between harmonious human structures, no matter their differences. Keeping track of these classifications is fundamental to harnessing the innovative prowess of industry leaders, meta-commanding global economic navigation, and fostering global sustainable technological integration. [1.].

HUMAN SYSTEMS INTEGRATION

Quality standards development

Sustainable manufacturing practices, rooted in environmental considerations, apply to technologically advanced and intensified competition [1]. Smaller organizations were very flexible with the intensity of adopting these standards with the competition. Efforts from suppliers illustrate an industry-wide shift towards sustainability, extending to areas like energy efficiency and infrastructure maintenance [3]. How can for example, wafer optimization and training advancements improve performance and reliability within optical connections? Integrating electronic control optimization techniques requires holistic technology and skilled personnel to drive product development transformation. Finnish systems engineering education framework offers system and engineering standards guidelines, emphasizing stakeholder requirements to ensure the training models remain relevant [4].

Industry stakeholder alignment

In continuous development, particularly in sectors like Fashion, the modern education engineering system is bound by the competitive challenge of keeping the pace [5]. Diamond extending business strategies, such as training simulations, offer potential solutions [6]. Concurrently, as industries demand technologies for Smart Manufacturing, educational curricula must impart theoretical knowledge and practical skills to students with industry-standard [4]. Sustainability challenges in global development demand a curriculum on solar energy, health protocols, and system upkeep. Though the ever-evolving life sectors evolving, the innovations could present opportunities for industries' research alignment throughout the organizational culture change by reverse engineering and optimizing the systems [2]. Emphasizing eco-friendly practices in water and smart wafer control until the water tap, prioritizes the Earth. With many solutions to climate change already in place, smart manufacturers were shifting focus. Nevertheless, these manufacturers play a critical role in maintaining high standards across the supply chain.

Training for technology innovation management

The specialized demands of manufacturing highlight the value of industry-focused educational content. It is essential that curricula seamlessly blend academic theory with intersection less setting to industrial use. Thus, education for most advanced innovation management roles is possible through science. Engineering education to technology has requirements for the synergy between combining structures with systems engineering. Synergizing system operations is of structural design is not affected by intersecting factors. By default, modern technology engineering education is coupled with endless innovations. The Internet of Things archives control the current business landscape within systems [7]. The big ascendancy of progressive e-commerce mechanisms emphasizes the urgency for businesses to grab the narrow points and connect to innovations. Design is not a word of user experience or infringement of the copyright but has seamless operations requirements for inspired design results with education. The incorporation of state-of-the-art platforms highlights examples. For example, systems applications and products courses in education that reflect the dynamic shift in business practices and strategic orientations for students to apply new management with systems, applications, and products in data processing high-performance analytic appliance.

Smart integrative solutions are relative

Integrating Industry 4.0

The manufacturing process's digitalization necessitates a systematic approach to ensure adaptability and efficiency. Implementing real-time feedback mechanisms in an industry setting is an educative tool for real-time rectifying in tackling glitches. Manufacturers can capitalize on independent subsystems' flexibility by integrating a modular design approach, ensuring seamless updates and replacements. The audits and reviews form the cores of the system design with decoupling. This comprehensive documentation captures the design process, providing a foundation for future initiatives. At its core, the culture of innovation is recognizable from the continuous engineering of solutions supporting intersectionally accessible education adapting to the future. [8]

Infusing traditional curriculum

Modern engineering tools fluctuate with the dynamic demands of the manufacturing sector. As a core between theory and practice, simulation labs with the pipeline afford customers an immersive experience; while, simulating real-world challenges is pedagogical in industry education [9]; [10]; [11]. Peer reviews could refine collective field visit experiences to view industry practices, while continuous industry efforts for collaboration does not form silos that transdisciplinary would differentiate the industry from education. Industry collaborative initiatives for guest lectures could infuse the curriculum content for industries with rich, experiential knowledge with complete independence to industrial protocols with continuous assessment, abandoning traditional examination for the culture of continual learning and problem-solving. Learning and motivation have a place; they remain paradoxical pitfalls between excellent learning, studying, and teaching processes.

Adapting synchronized setting for education

The fusion of service and manufacturing portends a transformative shift in manufacturing in a regionally free setting until it is properly regulated. Database service infrastructure fortifies manufacturing execution systems capabilities and maintains its fluidic data exchange and synchronized operations, creating a cohesive systems appliance with indexing [12]. Instead of the aforementioned waferwaffle example this integration heightens operational reasoning with black box analysis [13]. The versatility of the manufacturing service platform, for example survey, localizes in the complete management of languages and frameworks for adaptability to the research laboratories forming responsible a digital ocean. Database database-service-as-a-service data protection protocols initiatives safeguard critical data sensitivity that may prove to be a complicating factor without a design involving, for example, feature aggregation in synergy with the open-ended structure. The service toolkit in manufacturing operations has initiated a manufacturing standard has characterized by precision for innovating for enterprise resource planning systems of future. Promising manufacturing can help reveal the less visible parts of the engineering curriculum by adapting to the industry trends in selective scenarios. The rise of innovative approaches to the engineering curriculum aligns with the current shift towards higher quality to support industry in certification adoption.

The education sector development shows quality in systems design aligning with artificial intelligence with aerospace due to its popularity of design studies, e.g., [14]; [15]. The detailed analysis of the classification of the development state to the sanctuary of the enchantress of containerization requires more design studies. The importance of advancing training and meaningful learning for an efficient control system is, to adapt to another industry’s requirements to respond to its responsible development requirements. The human-machine interaction in the software domain relates to the designs on this framework, shifting to explainable training with innovation on various platforms [16]. Modern autonomous systems prioritizing adaptability to develop industrial facilities considers safety for example [17]. Safety becomes central to the axiomatic design, built on independence and information axioms to address the reliable system design [18]. Designs center on functional needs and design parameters, with system-specific frameworks for instance in aerospace. Benefiting from improving a physiological testing for a remote sensing by training simulations in advanced environments [19]; [20]. Studies aim to improve system effectiveness and safety by designing simulations with physics, like within FPGA-based boundaries [21], with wishes to start tracking and surrounding quantum computing aerospace centered very quickly.

RESULTS: PRODUCT LIFECYCLE STRATEGIES

Lifecycle management strategies for Offshoring

The analysis revealed the following key geographical preferences for offshoring different business activities:

a. Manufacturing offshoring gravitated towards Central Europe, Southwestern Europe, East/South Asia, North America

b. R&D offshoring preferences included Northwestern/Central Europe, South Asia, Nordic region

Proximity proves important, with Nordic/Baltic countries offering lower logistical hurdles. However, South Asia presents talent pool benefits despite unique operational challenges.

Integrating Global Trade Frameworks

Classifying global economic activities related to offshoring underscores the value of international standards like ISIC. Connections emerge between regional approaches (ISIC: NAICS, NACE, ANZSIC, etc.), informing tough trade and manufacturing strategies.

Case Study: Sustainable Product Development

A case study of a universal sustainable product line demonstrates integrating eco-friendly design with global marketability. Energy efficiency, responsible sourcing, recyclability, and standardized components align with international benchmarks. This showcases strategies for unifying development protocols across borders.

RECOMMENDATIONS

Key recommendations for manufacturers include:

a. Consider geographical pros/cons for offshoring specific activities

b. Leverage international classification systems customer

c. Design sustainable product lines adaptable to global

d. Participate in developing local training ecosystems

While exploratory, the analysis provides a foundation for data-driven decision making on globalization strategies, sustainability integration, and training innovation.

INTERPRETATION

The results show Finnish manufacturers' offshoring practices and alignment with global sustainability standards, while sustainability is of significant interest to the industry.

Technological integration, in the form of simulation, data analysis, and additive manufacturing for a case product of a system, emerges, requiring manufacturing offshoring. However, the same emphasis should be observed in R&D offshoring, suggesting different strategic considerations from the design built from the global innovation hub.

As reflected in the design paradigm, training engineering for innovative transportation, incorporating energy efficiency and eco-friendly considerations were firsthand considered globally. Environmental certifications, while valuable, were not uniformly adopted, indicating challenges for smaller entities requiring adaptation to international laws. Geographical preferences for offshoring vary, and businesses must navigate a complex global economic landscape with various classification systems. The results guide Finnish manufacturing development in decision-making on offshoring and integrating sustainability into their operations from the case example, especially in training engineering and various features in complex systems engineering.

DISCUSSION

The comprehensive data and research underscore the importance of human systems integration for understanding and predicting the behaviors of businesses considering globalization [22]. The drive for sustainable manufacturing practices and R&D considerations seen in the EMS data lays groundwork for future enterprises.

Cooperation between countries is intrinsically tied to policy compatibility, suggesting a need for standardized design and manufacturing practices aligned with recognized frameworks such as ISIC rather than solely regional approaches [1]. The findings indicate the curriculum for emerging technologies like containerization could align more closely with customer requirement management when the emphasis is on sustainable practices. Simulation, prototyping, and additive manufacturing require integration to ensure long-term viability and training innovation semantics because it does not really mean much in current industry setting [12]; [1].

As the future of engineering education is tethered to sustainable digital platforms, blending containerization and international standardization forms a transformative opportunity [23]. The EMS analysis showed proximity advantages for nearshoring to Nordic clusters, while talent incentives pull certain activities towards South Asia. This demonstrates how the future of autonomous systems will involve innovation between advanced manufacturing techniques and localized training needs [24].

As exponential industrial growth introduces new complexities, equipping the next generation of engineers with the requisite knowledge and strategies in design is imperative [25]. The EMS findings positioned training's role in risk detection and management as intertwined with sustainability initiatives. Decoupling legacy systems while nurturing new solutions will shape development trajectories [26].

When assessing emerging autonomous technologies, continuous innovation is crucial but must consider potential sustainability challenges. Adhering to standardized norms enhances communication reliability and safety with Certified environmental management system (ISO 14001 or EMAS) along with Quality management system key performance indicators [28] [29].

Implementing human-centered training management elevates system intelligence, as seen in the evolution of responsible development initiatives over time [30-31]. The analysis indicates manufacturing technology progression towards regional industrial revolutions must keep industrial metaverse safe.

Having the initial data for global industrial simulation, this research still lacks generalization to industry, training's expanding, and technology role in risk analysis and mitigation for smart manufacturing. Mismatches in existing containerization pose threats to infrastructure, necessitating assessment updates [32]. Further work should explore autonomous modules for developing smarter systems. Manufacturing advancements like virtual training enhance supply chain agility. Component-level design explorations could examine climate resilience to align with Industry 5.0 aspirations, despite not being an explicit focus of past EMS analysis.

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