Industry 4.0 technologies adoption and obstacles in manufacturing SMEs – challenges for strategy and organisational learning

Journal of Workplace Learning

69

Received 23 May 2025
Revised 25 September 2025
8 December 2025
Accepted 12 December 2025

Pirjo Yli-Viitala and Petri Helo
School of Technology and Innovations, University of Vaasa, Vaasa, Finland

Abstract

Purpose – This study aims to examine the adoption of key Industry 4.0 technologies, perceived obstacles and the role of organisational learning in manufacturing small and medium-sized enterprises (SMEs). It also explores how contingency factors such as employee count, turnover, research and development (R&D) spending and technological intensity influence adoption and obstacle severity.

Design/methodology/approach – A quantitative survey of 95 Finnish manufacturing SMEs was conducted. Hierarchical clustering identified typologies of technologies and obstacles, and multivariate analyses tested the effects of contingency factors. Organisational learning theory was used to interpret the findings.

Findings – Two clusters of technologies and obstacles were identified. Technology clusters reflect stages of organisational learning, while obstacle clusters distinguish between internal learning needs and external strategic coordination demands. Employee count and R&D spending were significantly associated with adoption, but not obstacle severity.

Originality/value – This study provides a unified empirical framework and a learning-based interpretation of SME digital transformation.

Keywords Industry 4.0 technologies, Contingency factors, Organisational learning, Obstacles, Survey, SMEs

Paper type Research paper

1. Introduction

Originally a German government initiative, Industry 4.0 (I4.0) is now a key driver of industrial transformation. To thrive in this environment, small and medium-sized enterprises (SMEs) must go beyond technology adoption and develop organisational learning capabilities for continuous adaptation and strategic renewal (Saadah and Hendarman, 2022). Organisational learning is seen as a critical enabler of successful I4.0 adoption, helping firms to rethink routines, challenge assumptions and adapt practices (Cheng *et al.*, 2024; Lenart-Gansiniec, 2019).

This study investigates the adoption I4.0 technologies, perceived obstacles and the influence of contingency factors in manufacturing SMEs. It applies organisational learning theory to interpret how different technologies and obstacles reflect varying learning demands and stages.

Funding: European Regional Development Fund, A76549.

Journal of Workplace Learning
Vol. 38 No. 9, 2026
pp. 69-86
Emerald Publishing Limited
1366-5626
DOI 10.1108/JWL-05-2025-0150

The research addresses the following questions:

RQ1. What are the primary I4.0 technologies adopted in manufacturing SMEs?

RQ2. What are the primary obstacles to I4.0 adoption in manufacturing SMEs?

RQ3. What is the influence of contingency factors on the degree of I4.0 adoption and related obstacles?

In this context, the *degree of adoption* refers to the extent to which different I4.0 technologies have been implemented by SMEs, based on self-reported use. *Obstacles* are perceived barriers that hinder technology adoption, categorised by their constraining nature.

Previous studies have typically examined themes separately, focusing either on technologies (Jankowska *et al.*, 2023; Zheng *et al.*, 2023; Baio Junior and Carrer, 2022; Zheng *et al.*, 2020), obstacles (Rahman *et al.*, 2025; Aditya *et al.*, 2021; Gonzales *et al.*, 2022; Javaid *et al.*, 2023) or contingency factors (Tortorella *et al.*, 2021b; Tortorella *et al.*, 2020a; Rossini *et al.*, 2019). Few have integrated them into a single framework or applied organisational learning theory in the SME context.

This study addresses that gap by using hierarchical clustering to identify data-driven typology of technologies and obstacles, interpreted though organisational learning theory. While previous studies have explored I4.0 adoption in SMEs in countries such as Germany (Müller and Voigt, 2018), Italy (Rossini *et al.*, 2019) and Poland (Jankowska *et al.*, 2023), research in the Nordic context remains limited. By focusing on Finnish manufacturing SMEs, this study also provides insights from an underexplored national context in digitalisation research. The findings support SME decision-makers and policymakers in identifying relevant technologies, anticipating obstacles and aligning support measures with firm-specific learning needs and constraints.

The paper proceeds as follows. Firstly, we review the theoretical background. Then, the data and methods are presented, followed by the empirical results. The findings are discussed through the lens of organisational learning, and finally, the conclusions outline theoretical contributions and practical implications.

2. Theoretical background

To analyse the theoretical background and prior related works, we review some advanced on I4.0 technologies, related obstacles and relevant contingency factors in SMEs. Organisational learning is used as a unifying lens to understand how firms adopt and internalise digital transformation.

2.1 Organisational learning and Industry 4.0 technologies

Originally introduced in Germany in 2011, I4.0 emphasises advanced, connected and human-centred manufacturing. Commonly cited technologies include additive manufacturing, artificial intelligence (AI), automation and industrial robots, big data analytics, blockchain, cloud technology, cyber-physical systems, Internet of Things, simulation and visualisation (Ghobakhloo *et al.*, 2022; Zheng *et al.*, 2021). Although no unified list exists, similar technologies appear across studies (e.g. Bosman *et al.*, 2019; Fettermann *et al.*, 2018) (Table 1). These technologies vary in complexity and maturity, and adoption remains uneven across SMEs.

Organisational learning theory helps explain this variation. Learning is seen as a multilevel process involving knowledge acquisition, sharing, interpretation and institutionalisation (Crossan *et al.*, 1999; Huber, 1991). Adopting complex technologies requires not only technical competence but also the ability to embed new knowledge into

Table 1. Acknowledged I4.0 enabling technologies

I4.0 enabling technologies	Zheng *et al.* (2021)	Salvadorinho and Teixeira (2021)	Torres da Rocha *et al.* (2022)	Ghobakhloo *et al.* (2022)	Kumar *et al.* (2020)
Internet of things (incl. IoT)	✓	✓	✓	✓	✓
Cloud technology	✓	✓	✓	✓	✓
Big data and analytics (incl. BDA)	✓	✓	✓	✓	✓
Visualisation technology (incl. AR, VR)	✓	✓	✓	✓	✓
Simulation and modelling	✓		✓	✓	
Blockchain	✓		✓	✓	
Artificial intelligence (incl. AI)	✓		✓	✓	
Cyber-Physical systems (incl. CPS)	✓	✓	✓	✓	✓
Automation and industrial robot	✓	✓	✓	✓	✓
Additive manufacturing (incl. AM)	✓	✓	✓	✓	✓

Source(s): Authors' own work

routines. Firms differ in absorptive capacity, which affects their readiness to implement different technologies (Cohen and Levinthal, 1990).

More accessible technologies like cloud computing and big data analytics may require only incremental learning, while advanced systems, such as AI or simulation often demand deeper organisational change. Although prior studies cluster technologies by adoption frequency (dos Santos *et al.*, 2020; Tortorella *et al.*, 2021a), few frame this within a learning perspective, particularly in SMEs.

2.2 Organisational learning and obstacles to Industry 4.0

I4.0 adoption is also hindered by various obstacles (Table 2), often classified as intrinsic (internal) or extrinsic (external) obstacles (Chauhan *et al.*, 2021; Jabbour *et al.*, 2016). Intrinsic obstacles include limited resources, employee resistance, organisational culture, uncertainty and technological complexity (Stentoft *et al.*, 2021; Horváth and Szabó, 2019). Extrinsic obstacles involve data security, cooperation gaps, demand uncertainty, competition, lack of best practises, regulations, infrastructure deficiencies and insufficient policy support (Horváth and Szabó, 2019; Müller and Voigt, 2018).

From a learning perspective, intrinsic obstacles often reflect limitations in knowledge acquisition, leadership support or cultural readiness for change. These barriers may hinder double-loop learning and the development of adaptive routines (Vera and Crossan, 2004). While extrinsic barriers lie outside the firm, they still require learning through strategic scanning, policy interpretation or inter-organisational coordination. Although obstacles have been clustered thematically (Leitão *et al.*, 2022; Hobscheidt *et al.*, 2021), few studies explicitly examine theme as learning-related challenges in SMEs.

2.3 Contingency factors and learning conditions

Firm-specific factors such as size, research and development (R&D) intensity and technological environment influence the capacity to adopt I4.0 technologies and to

Table 2. Overarching dimensions of the obstacles to I4.0 adoption

I4.0 obstacles	References
Lack of resources	Attiany *et al.* (2023); Sharma *et al.* (2023); Alsaadi (2022); Chauhan *et al.* (2021); Stentoft *et al.* (2021); Masood and Sonntag (2020); Pirola *et al.* (2019); Rauch and Vickery (2020); Zangiacomi *et al.* (2020); Horváth and Szabó (2019)
Employees' resistance to change, lack of management and leadership	Attiany *et al.* (2023); Sharma *et al.* (2023); Chauhan *et al.* (2021); Soluk and Kammerlander (2021); Rauch and Vickery (2020); Horváth and Szabó (2019)
Organisation culture and structure	Attiany *et al.* (2023); Ko *et al.* (2020); Pirola *et al.* (2019); Rauch and Vickery (2020); Horváth and Szabó (2019)
Unclear consequences of I4.0	Attiany *et al.* (2023); Sharma *et al.* (2023); Alsaadi (2022); Chauhan *et al.* (2021); Pirola *et al.* (2019); Rauch and Vickery (2020); Horváth and Szabó (2019); Müller and Voigt (2018)
Difficulties in integration, internal infrastructure, or complexity of technological factors	Attiany *et al.* (2023); Alsaadi (2022); Ko *et al.* (2020); Masood and Sonntag (2020); Zangiacomi *et al.* (2020); Pirola *et al.* (2019)
Lack of strategy	Attiany *et al.* (2023); Sharma *et al.* (2023); Chauhan *et al.* (2021); Pirola *et al.* (2019); Zangiacomi *et al.* (2020); Horváth and Szabó (2019)
Data security (cyber security) and data ownership issues	Attiany *et al.* (2023); Sharma *et al.* (2023); Alsaadi (2022); Chauhan *et al.* (2021); Rauch and Vickery (2020); Horváth and Szabó (2019)
Lack of cooperation in supply chain	Sharma *et al.* (2023); Chauhan *et al.* (2021); Masood and Sonntag (2020); Pirola *et al.* (2019); Rauch and Vickery (2020); Zangiacomi *et al.* (2020); Arcidiacono *et al.* (2019); Horváth and Szabó (2019)
Demand uncertainty	Sharma *et al.* (2023) Chauhan *et al.* (2021); Müller and Voigt (2018)
Competitive pressure or shortcomings in tendering	Sharma *et al.* (2023); Zangiacomi *et al.* (2020); Horváth and Szabó (2019)
Lack of best practices and case examples	Ko *et al.* (2020); Zangiacomi *et al.* (2020)
Regulations and standards	Sharma *et al.* (2023); Chauhan *et al.* (2021); Rauch and Vickery (2020); Arcidiacono *et al.* (2019); Horváth and Szabó (2019)
Inadequate infrastructure	Attiany *et al.* (2023); Alsaadi (2022); Chauhan *et al.* (2021)
Lack of policy level support	Alsaadi (2022); Chauhan *et al.* (2021); Rauch and Vickery (2020); Zangiacomi *et al.* (2020)

Source(s): Authors' own work

overcome obstacles (Rossini *et al.*, 2019; Tortorella *et al.*, 2019). These contingency factors shape how firms absorb and institutionalise knowledge (Lionzo and Rossignoli, 2013; Cohen and Levinthal, 1990). Smaller firms may rely on informal learning, while larger ones can invest in structured programmes (Ivaldi *et al.*, 2022; Lionzo and Rossignoli, 2013). Similarly, low R&D spending may limit innovation but encourage the efficient use of existing tools. Although contingency factors have been statistically linked to adoption (Tortorella *et al.*, 2020a), their role in enabling or constraining learning processes in SMEs is less explored.

2.4 Organisational learning as a theoretical lens adoption

Organisational learning provides an integrative theoretical foundation for this study, as it helps explain how SMEs acquire, share and embed knowledge necessary for I4.0 adoption. A central distinction is between lower-level learning, which supports incremental improvements, and higher-level or double-loop learning, which questions and modifies existing assumptions, strategies and routines (Vera and Crossan, 2004).

There is ongoing debate in the literature regarding the relationship between organisational learning and digital transformation. One view considers organisational learning as a prerequisite for capability development, whereby firms must first build learning capacity to absorb technological (Vial, 2019). Another view, rooted in dynamic capabilities theory, suggests that digitalisation itself transforms learning processes by altering how firms experiment, adapt and innovate (Teece, 2018). These contrasting views suggest that firms must not only build learning capacity to enable digital change but also remain responsive to how digitalisation itself transforms the nature of learning.

3. Material and methods

This study is based on a quantitative survey of 95 Finnish manufacturing SMEs. The survey captured the adoption of 10 I4.0 technologies, perceived obstacles and four contingency factors: number of employees, turnover, R&D spending and technological intensity.

3.1 Sample selection and survey development

The sample consisted of SMEs following EU definitions (Eurostat, 2026a), with Chief Executive Officers (CEOs) or similar roles as respondents to ensure data reliability.

The questionnaire included firm background, technology use (four-point scale) and perceived obstacles (five-point scale). Technologies and obstacles were drawn from prior research (Table 1, Table 2).

Ten Likert-scale items measured adoption, and sixteen measured intrinsic and extrinsic obstacles. Contingency factors were included as standard firm-level variables. For the cluster analyses, adoption and obstacle items were z-standardised and entered as input variables, without further aggregation. This ensured that each survey item mapped directly onto the respective construct and that differences in scale units did not bias the clustering solution.

The questionnaire was pre-tested with practitioners and academics, leading to minor adjustments. Table 3 provides an overview of the survey questionnaire. No ethical clearance was required under The Finnish National Board on Research Integrity (TENK) guidelines.

The online survey was open between April and June 2021. Of 1,359 firms contacted via Alma Talent's database, 113 responded, resulting in a response rate of 8.3%, which is comparable to other studies (Zheng *et al.*, 2020, 11%; Verhovnik and Duh, 2021, 7.5%).

Table 3. An overview of the survey questionnaire

Part	Aim	No. of elements	Answer type
1	Provide data on respondents and companies (position, industry, size, years in operation, turnover spent on R&D)	5	4 Multiple choice; 1 open-ended
2	Provide the adoption degree of I4.0 technologies	10	Four-point scale
3	Provide the degree of obstacles	14	Five-point scale

Source(s): Authors' own work

After exclusions, the final data set comprised 95 responses from 93 companies. A chi-square test was used to assess non-response bias.

Respondents mostly held top management roles. SMEs were categorised by size based on EU recommendation 2003 / 361, R&D spending and technology intensity based on Eurostat classifications (Eurostat, 2026b). Table 4 presents sample characteristics.

Cronbach's alpha values (0.67 for adoption, 0.86 for obstacles) exceeded the threshold of 0.6 (Van Griethuijsen *et al.*, 2015), and no items improved reliability when removed.

3.2 Sample and method bias

To minimise common method bias, anonymity was ensured and questions left open to respondents' interpretation. It should be noted that the survey focused exclusively on respondents from Finnish manufacturing SMEs, which helped to ensure the legitimacy and validity of their responses. Harman's single factor test showed no concerning variance (16.3%, well below the 50% threshold), suggesting minimal method bias.

Table 4. Sample ($n = 95$)

Position in SME	Frequency	%
Lead management	63	66.3
Key personnel	30	31.6
Number of employees		
1–10	28	29.5
11–50	37	38.9
51–249	29	30.5
Annual turnover		
< 2 M€	34	35.8
2 M€ < 10 M€	34	35.8
10 M€ < 50 M€	25	26.3
Percentage of turnover spent on R&D		
≤ 2%	53	55.8
> 2%	31	32.6
Technological intensity		
High-technology and medium-high-technology	29	30.5
Medium-low-technology and low-technology	66	69.5

Source(s): Authors' own work

3.3 Data clustering

To identify key I4.0 technologies adopted and the related obstacles (RQ1, RQ2), two clustering analyses were performed. Following the method applied in Tortorella *et al.* (2021a), 10 digital technologies were used as clustering variables. Ward's hierarchical method with the squared Euclidian distance metric was employed to determine the appropriate number (k) of clusters based on the adoption degree of I4.0 technologies. The same clustering method applied to the perceived severity of obstacles.

3.4 Data analysis

The analyses were conducted using IBM SPSS Statistics (version 29.0.2.0). A Multivariate Analysis of Variance (MANOVA) with Wilks' lambda test was used to test the influence of contingency factors on the degree of I4.0 adoption and the level of perceived obstacles (*RQ3*).

Before running MANOVA, assumption tests (Zach, 2021) confirmed multivariate normality, equal variances and absence of outliers. Likert-scale items were treated as continuous variables, following established practice (Norman, 2010). This approach was supported by the results of normality and variance tests and was appropriate for the multivariate design. While non-parametric and ordinal methods (such as proportional odds logistic regression) are valid in certain contexts, the parametric approach enabled comparability across multiple outcomes. With at least 20 observations per group, the assumption of normality was considered reasonably satisfied. Box's M test ($p > 0.05$) supported equal covariance. As the Mahalanobis distance was below the threshold of 0.001, no extreme outliers were detected. Overall, the data met the assumptions required for MANOVA.

MANOVA was conducted using the four contingency factors as independent variables. Following Tortorella *et al.* (2021a), the first test used "highly adopted I4.0 technologies" as dependent variables, and the second used six "highly constraining obstacles".

Following the MANOVA tests, univariate analyses were performed to examine each dependent variable individually. Levene's test confirmed equal for all variables except cloud technologies in relation to number of employees ($p = 0.041$). However, Welch's test produced consistent results, indicating that the assumption of equal variances between groups was reasonably met. Univariate Analysis of Variance (ANOVA) tests were then carried out for the cases where MANOVA produced significant F-values.

4. Results

Hierarchical clustering of the adoption degree of ten I4.0 technologies revealed two clusters (Figure 1). The "highly adopted I4.0 technologies" cluster comprised *big data analytics*, *visualisation technologies (AR, VR)*, *IoT* and *cloud technologies*, while the "lowly adopted I4.0 technologies" included six less commonly adopted technologies: *block chain*, *cyber-physical systems*, *simulation and modelling*, *additive manufacturing*, *AI* and *automation and industrial robots*.

A similar clustering of obstacles revealed two clusters (Figure 2). The "highly constraining obstacles" included *lack of resources*; *employee resistance to change*, *lack of management and of leadership*; *organisational culture and structure*; *unclear consequences of I4.0*; *difficulties in integration, internal infrastructure, or complexity of technological factors*; and *lack of strategy*. These largely reflect internal organisational challenges.

The "lowly constraining obstacles" comprised *data security and ownership issues*; *lack of cooperation in supply chain*; *demand uncertainty*; *competitive pressure or shortcomings in tendering*; *lack of best practises and case examples*; *regulations and standards*; *inadequate infrastructure* and *lack of policy level support*, which are mainly external in nature.

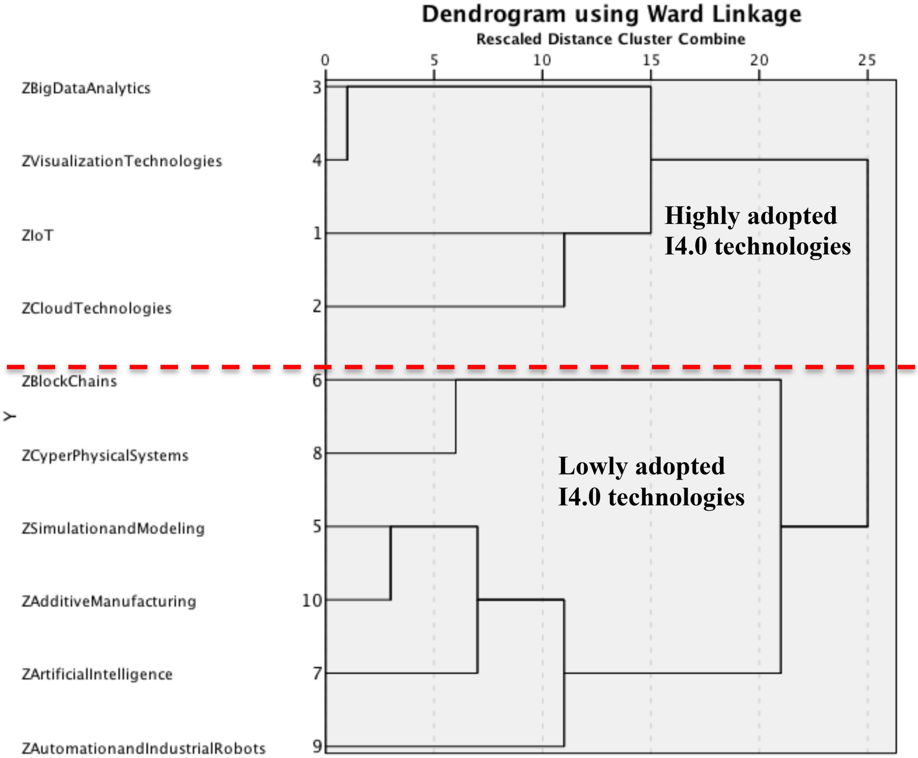

Figure 1. The Ward clustering method applied to illustrate the adoption degree of I4.0 technologies through a dendrogram
Source: Authors' own work

The cluster names are descriptive summaries based on the empirical differences in adoption levels observed between the groups.

MANOVA results (Table 5) indicated that *number of employees* and *R&D spending* had a statistically significant influence on the degree of adoption of the I4.0 technologies ($p < 0.05$), while *annual turnover* and *technological intensity* did not.

None of the contingency factors were significantly associated with the severity of obstacles ($p > 0.05$) (Table 5).

ANOVA results (Table 6) indicated that the level of the *number of employees* (i.e. 1–10, 11–50 and 51–249 employees) had a statistically significant effect on the adoption of *cloud technologies* and *big data analytics*. Use of *cloud technologies* was significantly higher in micro-sized SMEs compared to medium-sized firms, while adoption of *big data analytics* was significantly higher in both micro- and small-sized SMEs than in medium-sized ones. No significant differences were found between micro- and small-sized SMEs. In addition, no significant effects were observed for *Internet of Things* or *visualisation technologies (AR, VR)*.

The level of *percentage of turnover spent on R&D* (i.e. $\leq 2\%$, $> 2\%$) had a statistically significant effect on the adoption of *big data analytics* and *visualisation technologies (AR, VR)* (Table 6). The use of *big data analytics* was significantly higher among SMEs spending $\leq 2\%$

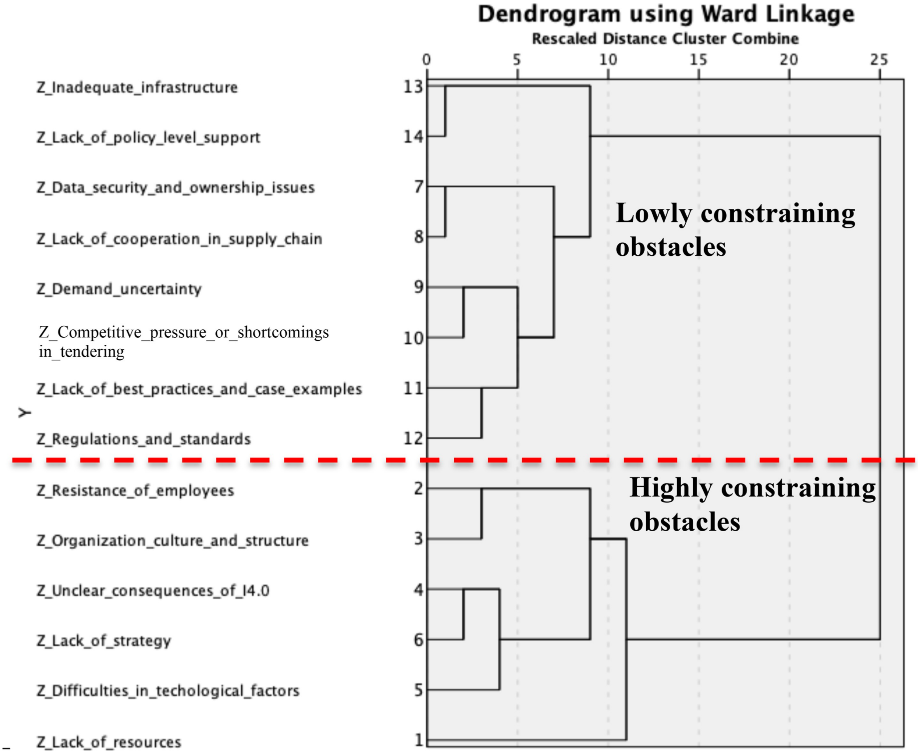

Figure 2. The Ward clustering method applied to illustrate the degree of obstacles associated with the adoption of I4.0 technologies through a dendrogram
Source: Authors' own work

on R&D compared to those spending more than 2%. Similarly, the adoption of *visualisation technologies (AR, VR)* was significantly higher among SMEs with lower R&D spending. No significant differences were found for *Internet of Things* or *cloud technologies*.

Table 7 presents a summary of the results concerning the contingency factors.

These findings overview adoption and challenges among Finnish manufacturing SMEs. A chi-square test comparing respondents and non-respondents based on company size showed a significant difference in the detailed classification (micro, small, medium; $\chi^2 = 8.01$, $p = 0.018$), but not in the aggregated classification (micro versus others; $\chi^2 = 0.00$, $p = 1.00$).

5. Discussion

This study advances understanding of I4.0 adoption in manufacturing SMEs by interpreting empirical patterns through organisational learning theory. The two clusters of I4.0 technologies reflect different levels of learning maturity. Widely adopted technologies indicate more advanced stages of learning. In such stages, knowledge has already been acquired, tested and institutionalised (Galy and LeMaster, 2006; Levine, 2001; Crossan *et al.*, 1999). In contrast, the lowly adopted cluster includes technologies that demand more

Table 5. MANOVA results using Wilk's lambda test

Contingency factors	Highly adopted I4.0 technologies Value	F	p-value	Contingency factors	Highly constraining obstacles Value	F	p-value
Number of employees	0.852	2.219*	0.028	Number of employees	0.925	0.570	0.864
Annual turnover	0.893	1.266	0.264	Annual turnover	0.927	0.548	0.880
Percentage spent on R&D	0.881	2.674*	0.038	Percentage spent on R&D	0.891	1.568	0.168
Technological intensity	0.935	1.569	0.189	Technological intensity	0.929	1.114	0.361

Note(s): *p-value < 0.05, **p-value < 0.01
Source(s): Authors' own work

Table 6. Univariate ANOVA tests for the I4.0 technologies with high adoption rates

Highly adopted I4.0 technologies	Number of employees 1–10	11–50	51–249	ANOVA value	p-value	Significant pairwise comparisons (Tukey's test)	Turnover spent on R&D ≤ 2%	> 2%	ANOVA value	p-value
Internet of things	2.786	2.568	2.207	2.055	0.134		2.755	2.290	3.596	0.061
Cloud technologies	1.893	1.541	1.241	3.313*	0.041	(1, 3)*	1.642	1.387	1.305	0.257
Big data analytics	3.429	3.216	2.724	6.033**	0.003	(1, 3)** (2, 3)*	3.264	2.839	5.530	0.021*
Visualisation technologies (AR, VR)	3.289	3.027	2.828	2.324	0.104		3.245	2.774	7.869	0.006**

Note(s): *p -value < 0.05, **p -value < 0.01
Source(s): Authors' own work

Table 7. Summary of the results related to contingency factors

Cluster	I4.0 technologies and obstacles	Number of employees	Annual turnover	Percentage of turnover spent on R&D	Technological intensity
Highly adopted Industry 4.0 technologies	IoT	–	–	–	–
	Cloud technologies	SMEs with 1–10 employees > SMEs with 51–249 employees	–	–	–
	Big data analytics	SMEs with 1–10 and 11–50 employees > SMEs with 51–249 employees	–	SMEs that spent ≤ 2% on R&D > SMEs that spent > 2% on R&D	–
	Visualization technologies (AR, VR)	–	–	SMEs that spent ≤ 2% on R&D > SMEs that spent > 2% on R&D	–
Highly constraining obstacles	Lack of resources	–	–	–	–
	Employees' resistance to change, lack of management and of leadership	–	–	–	–
	Organizational culture and structure	–	–	–	–
	Unclear consequences of I4.0	–	–	–	–
	Difficulties in integration, internal infrastructure, or complexity of technological factors	–	–	–	–
	Lack of strategy	–	–	–	–

Note(s): Empty cells in the table indicate a lack of statistically significant differences, and therefore, these differences were disregarded
Source(s): Authors' own work

extensive learning efforts and organisational transformation, suggesting earlier learning stages. This interpretation links clustering to organisational learning theory and highlights adoption as a learning-dependent process. While this typology is helpful, it may oversimplify adoption realities, as some SMEs may selectively skip stages or outsource capability development.

The obstacle clusters show a parallel structure. The highly constraining obstacles reflect challenges that may require more advanced, systematic organisational learning and change. Vera and Crossan (2004) discussed how such learning involves questioning underlying assumptions and adapting organisational routines. These intrinsic barriers may require shared understanding, continuous feedback and effective internal communication, which are central mechanisms in organisational learning (Huber, 1991). This aligns with literature on workplace learning, which emphasises the role of reflection, leadership support and collaborative practices in enabling employee learning and capability development (Ivaldi *et al.*, 2022; Lenart-Gansiniec, 2019). In contrast, the lowly constraining obstacles cluster may be less responsive to internal learning processes. Instead, these challenges often necessitate coordination with external networks or strategic repositioning. This typology highlights the importance of distinguishing between obstacles that demand internal development and those that call for strategic positioning.

The limited influence of structural contingency factors suggests that internal learning mechanisms, rather than structural characteristics, explain variation in how firms experience and manage barriers (Cheng *et al.*, 2024; Ivaldi *et al.*, 2022; Lenart-Gansiniec, 2019).

Taken together, the four clusters align with different organisational learning processes described in the 4I framework (Crossan *et al.*, 1999). High adoption and low obstacle severity suggest learning that has progressed towards integration and institutionalisation, whereas low adoption or high obstacle severity reflect earlier stages of intuition and interpretation and more exploratory learning demands.

5.1 Limitations

This study has limitations. The modest sample size ($n = 95$), although comparable to similar studies, may limit statistical power and increase the risk of Type II errors, particularly in the multivariate analyses. The Finnish context may limit generalisability, as SMEs benefit from strong public support for innovation and digitalisation, including targeted funding and advanced infrastructure (OECD, 2023). Voluntary participation may have introduced self-selection bias, as digitally engaged firms could be overrepresented. Despite a non-response bias test, the low response rate and observed differences mean bias cannot be fully excluded. Finally, clustering results may be sensitive to the choice of distance metric and linkage method. Although alternative metrics were not tested, evaluating multiple cluster solutions ($k = 2$–6) supported the robustness of the selected typology.

6. Conclusions

This study first identified the key I4.0 technologies adopted, the obstacles they face and the role of contingency factors. Clustering analysis revealed two clusters of technologies and two clusters of obstacles. Employee count and R&D spending influenced adoption, while turnover and technological intensity did not. None of the contingency factors affected obstacle severity.

6.1 Theoretical contribution

The study's theoretical contribution lies in developing a data-driven typology of technologies and obstacles interpreted through organisational learning theory. It links adoption clusters to different learning stages and shows how technology adoption can be seen as part of the learning processes within SMEs.

In addition, the study presents a learning-oriented way to understand obstacles by distinguishing between intrinsic and extrinsic challenges from the standpoint of organisational learning. These two types of obstacles call for different responses: intrinsic ones are often best addressed through internal learning and adaptation, while extrinsic ones may require strategic coordination beyond the organisation. This approach extends to earlier research, which typically categorised obstacles without linking them to how organisations learn and adapt.

Importantly, structural factors did not shape how obstacles were perceived, underscoring the centrality of internal learning processes in shaping how SMEs respond to the challenges of digital transformation.

6.2 Contribution to practice

The findings suggest that smaller firms may benefit from scalable or off-the-shelf solutions such as cloud or big data, while firms with limited R&D resources can still progress through accessible technologies. In addition, a learning-based typology of obstacles helps managers decide which barriers can be solved internally and which demand for strategic networking and external engagement.

SMEs can foster learning environments that reduce internal barriers by supporting employee training, encouraging shared reflection and enabling collaborative experimentation. Finally, the lack of association between contingency factors and perceived obstacles means that SMEs should focus on practices and culture that support organisational learning, not just in resources.

These insights support SME managers in evaluating their digital readiness and prioritising capability development. At the societal level, promoting SME digitalisation may contribute to regional resilience and economic competitiveness. Policymakers can use the results to better tailor support for SME needs, for instance by facilitating peer learning and knowledge-sharing.

6.3 Future research

Future studies could explore how SMEs build learning capabilities via mechanisms such as experimentation, feedback and leadership, and explore how these shape digital adoption across different contexts.

References

Aditya, B.R., Ferdiana, R. and Kusumawardani, S.S. (2021), "Identifying and prioritizing barriers to digital transformation in higher education: a case study in Indonesia", *International Journal of Innovation Science*, Vol. 14 Nos 3-4, pp. 445-460, doi: 10.1108/IJIS-11-2020-0262.

Alsaadi, N. (2022), "Modeling and analysis of industry 4.0 adoption challenges in the manufacturing industry", *Processes*, Vol. 10 No. 10, p. 2150, doi: 10.3390/pr10102150.

Arcidiacono, F., Ancarani, A., Di Mauro, C. and Schupp, F. (2019), "Where the rubber meets the road: Industry 4.0 among SMEs in the automotive sector", *IEEE Engineering Management Review*, Vol. 47 No. 4, pp. 86-93, doi: 10.1109/EMR.2019.2932965.

Attiany, M.S., Al-Kharabsheh, S.A., Al-Makhariz, L.S., Abed-Qader, M.A., Al-Hawary, S.I.S., Mohammad, A.A. and Rahamneh, A.A.A. (2023), "Barriers to adopt industry 4.0 in supply chains using interpretive structural modeling", *Uncertain Supply Chain Management*, Vol. 11 No. 1, pp. 299-306, doi: 10.5267/j.uscm.2022.9.013.

Baio Junior, A.A. and Carrer, M.J. (2022), “Adoption of industry 4.0 technologies: an analysis of small and medium-sized companies in the state of São Paulo, Brazil”, *Gestão and Produção*, Vol. 29 No. 122, doi: 10.1590/1806-9649-2022v29e122.

Bosman, L., Hartman, N. and Sutherland, J. (2019), “How manufacturing firm characteristics can influence decision making for investing in industry 4.0 technologies”, *Journal of Manufacturing Technology Management*, Vol. 31 No. 5, pp. 1117-1141, doi: 10.1108/JMTM-09-2018-0283.

Chauhan, C., Singh, A. and Luthra, S. (2021), “Barriers to industry 4.0 adoption and its performance implications: an empirical investigation of emerging economy”, *Journal of Cleaner Production*, Vol. 285, p. 124809, doi: 10.1016/j.jclepro.2020.124809.

Cheng, C.-H., Li, M.-H., Tang, B.-J. and Cheng, Y.-R. (2024), “The impact of knowledge management and organizational learning promotion in small and medium enterprises on the implementation of industry 4.0 and competitiveness”, *Administrative Sciences*, Vol. 14 No. 8, p. 161, doi: 10.3390/admsci14080161.

Cohen, W.M. and Levinthal, D.A. (1990), “Absorptive capacity: a new perspective on learning and innovation”, *Administrative Science Quarterly*, Vol. 35 No. 1, pp. 128-152, doi: 10.2307/2393553.

Crossan, M.M., Lane, H.W. and White, R.E. (1999), “An organizational learning framework: from intuition to institution”, *The Academy of Management Review*, Vol. 24 No. 3, pp. 522-537, doi: 10.5465/AMR.1999.2202135.

dos Santos, L.M.A.L., da Costa, M.B., Kothe, J.V., Benitez, G.B., Schaefer, J.L., Baierle, I.C. and Nara, E.O.B. (2020), “Industry 4.0 collaborative networks for industrial performance”, *Journal of Manufacturing Technology Management*, Vol. 32 No. 2, pp. 245-265, doi: 10.1108/JMTM-04-2020-0156.

Eurostat (2026a), “EU small and medium-sized enterprises: an overview”, available at: https://ec.europa.eu/eurostat/web/products-eurostat-news/-edn-20220627-1 (accessed 13 September 2025).

Eurostat (2026b), “Glossary: high-tech classification of manufacturing industries”, available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=lossary:High-tech_classification_of_manufacturing_industries (accessed 13 September 2025).

Fettermann, D.C., Cavalcante, C.G.S., Almeida, T.D.D. and Tortorella, G.L. (2018), “How does industry 4.0 contribute to operations management?”, *Journal of Industrial and Production Engineering*, Vol. 35 No. 4, pp. 255-268, doi: 10.1080/21681015.2018.1462863.

Galy, E. and LeMaster, J. (2006), “Organizational learning stages of assimilation, integration and optimization and their relationship with user satisfaction of enterprise resource planning systems”, *Journal of International Technology and Information Management*, Vol. 15 No. 4, pp. 60-76, doi: 10.58729/1941-6679.1182.

Ghobakhloo, M., Iranmanesh, M., Vilkas, M., Grybauskas, A. and Amran, A. (2022), “Drivers and barriers of industry 4.0 technology adoption among manufacturing SMEs: a systematic review and transformation roadmap”, *Journal of Manufacturing Technology Management*, Vol. 33 No. 6, pp. 1029-1058, doi: 10.1108/JMTM-12-2021-0505.

Gonzales, G., Costan, F., Suladay, D., Gonzales, R., Enriquez, L., Costan, E., Atibing, N.M., Aro, J.L., Evangelista, S.S., Maturan, F., Selerio, E. and Ocampo, L. (2022), “Fermatean fuzzy DEMATEL and MMDE algorithm for modelling the barriers of implementing education 4.0: insights from the Philippines”, *Applied Sciences*, Vol. 12 No. 2, p. 689, doi: 10.3390/app12020689.

Hobscheidt, D., Kühn, A. and Dumitrescu, R. (2021), “Derivation of socio-technical solution patterns for industry 4.0 problem classes”, *Procedia CIRP*, Vol. 100, pp. 301-306, doi: 10.1016/j.procir.2021.05.070.

Horváth, D. and Szabó, R. (2019), “Driving forces and barriers of industry 4.0: do multinational and small and medium-sized companies have equal opportunities?”, *Technological Forecasting and Social Change*, Vol. 146, pp. 119-132, doi: 10.1016/j.techfore.2019.05.021.

Huber, G.P. (1991), “Organizational learning: the contributing processes and the literatures”, *Organization Science*, Vol. 2 No. 1, pp. 88-115, doi: 10.1287/orsc.2.1.88.

Ivaldi, S., Scaratti, G. and Fregnan, E. (2022), “Dwelling within the fourth industrial revolution: organizational learning for new competences, processes and work cultures”, *Journal of Workplace Learning*, Vol. 34 No. 1, pp. 1-26, doi: 10.1108/JWL-07-2020-0127.

Jabbour, C.J.C., de Sousa Jabbour, A.B.L., Govindan, K., de Freitas, T.P., Soubihia, D.F., Kannan, D. and Latan, H. (2016), “Barriers to the adoption of green operational practices at Brazilian companies: effects on green and operational performance”, *International Journal of Production Research*, Vol. 54 No. 10, pp. 3042-3058, doi: 10.1080/00207543.2016.1154997.

Jankowska, B., Mińska-Struzik, E., Bartosik-Purgat, M., Götz, M. and Olejnik, I. (2023), “Industry 4.0 technologies adoption: barriers and their impact on polish companies’ innovation performance”, *European Planning Studies*, Vol. 31 No. 5, pp. 1029-1049, doi: 10.1080/09654313.2022.2068347.

Javaid, M., Khan, S., Haleem, A. and Rab, S. (2023), “Adoption of modern technologies for implementing industry 4.0: an integrated MCDM approach”, *Benchmarking: An International Journal*, Vol. 30 No. 10, pp. 3753-3790, doi: 10.1108/BIJ-01-2021-0017.

Ko, M., Kim, C., Lee, S. and Cho, Y. (2020), “An assessment of smart factories in Korea: an exploratory empirical investigation”, *Applied Sciences*, Vol. 10 No. 21, p. 7486, doi: 10.3390/app10217486.

Kumar, R., Singh, R.K. and Dwivedi, Y.K. (2020), “Application of industry 4.0 technologies in SMEs for ethical and sustainable operations: analysis of challenges”, *Journal of Cleaner Production*, Vol. 275, p. 124063, doi: 10.1016/j.jclepro.2020.124063.

Leitão, P., Queiroz, J. and Sakurada, L. (2022), “Collective intelligence in self-organized industrial cyber-physical systems”, *Electronics*, Vol. 11 No. 19, p. 3213, doi: 10.3390/electronics11193213.

Lenart-Gansiniec, R. (2019), “Organizational learning in industry 4.0”, *Problemy Zarzadzania*, Vol. 2 No. 2, pp. 96-108, doi: 10.7172/1644-9584.82.4.

Levine, L. (2001), “Integrating knowledge and processes in a learning organization”, *Information Systems Management*, Vol. 18 No. 1, pp. 1-13, doi: 10.1201/1078/43194.18.1.20010101/31262.4.

Lionzo, A. and Rossignoli, F. (2013), “Knowledge integration in family SMEs: an extension of the 4I model”, *Journal of Management and Governance*, Vol. 17 No. 3, pp. 583-608, doi: 10.1007/s10997-011-9197-y.

Masood, T. and Sonntag, P. (2020), “Industry 4.0: adoption challenges and benefits for SMEs”, *Computers in Industry*, Vol. 121, p. 103261, doi: 10.1016/j.compind.2020.103261.

Müller, J.M. and Voigt, K.-I. (2018), “Sustainable industrial value creation in SMEs: a comparison between industry 4.0 and made in China 2025”, *International Journal of Precision Engineering and Manufacturing-Green Technology*, Vol. 5 No. 5, pp. 659-670, doi: 10.1007/s40684-018-0056-z.

Norman, G. (2010), “Likert scales, levels of measurement and the ‘laws’ of statistics”, *Advances in Health Sciences Education*, Vol. 15 No. 5, pp. 625-632, doi: 10.1007/s10459-010-9222-y.

OECD (2023), *OECD SME and Entrepreneurship Outlook 2023*, OECD Publishing, Paris, doi: 10.1787/342b8564-en.

Pirola, F., Cimini, C. and Pinto, R. (2019), “Digital readiness assessment of Italian SMEs: a case-study research”, *Journal of Manufacturing Technology Management*, Vol. 31 No. 5, pp. 1045-1083, doi: 10.1108/JMTM-09-2018-0305.

Rahman, M., Emon, M.E.H., Antor, M.H., Haque, S.A. and Talapatra, S. (2025), “Identification and prioritization of barriers to industry 4.0 adoption in the context of food and beverage industries of Bangladesh”, *Benchmarking: An International Journal*, Vol. 32 No. 2, pp. 757-783, doi: 10.1108/BIJ-06-2023-0371.

Rauch, E. and Vickery, A.R. (2020), "Systematic analysis of needs and requirements for the design of smart manufacturing systems in SMEs", *Journal of Computational Design and Engineering*, Vol. 7 No. 2, pp. 129-144, doi: 10.1093/jcde/qwaa012.

Rossini, M., Costa, F., Tortorella, G.L. and Portioli-Staudacher, A. (2019), "The interrelation between Industry 4.0 and lean production: an empirical study on European manufacturers", *The International Journal of Advanced Manufacturing Technology*, Vol. 102 Nos 9-12, pp. 3963-3976, doi: 10.1007/s00170-019-03441-7.

Saadah, L. and Hendarman, A.F. (2022), "The relationship between new learning organization on human capital readiness of SMEs in Industry 4.0", *Devotion: Journal of Research and Community Service*, Vol. 3 No. 10, pp. 971-978.

Salvadorinho, J. and Teixeira, L. (2021), "Stories told by publications about the relationship between industry 4.0 and lean: systematic literature review and future research agenda", *Publications*, Vol. 9 No. 3, p. 29, doi: 10.3390/publications9030029.

Sharma, M., Raut, R.D., Sehrawat, R. and Ishizaka, A. (2023), "Digitalisation of manufacturing operations: the influential role of organisational, social, environmental, and technological impediments", *Expert Systems with Applications*, Vol. 211, p. 118501, doi: 10.1016/j.eswa.2022.118501.

Soluk, J. and Kammerlander, N. (2021), "Digital transformation in family-owned Mittelstand firms: a dynamic capabilities perspective", *European Journal of Information Systems*, Vol. 30 No. 6, pp. 676-711, doi: 10.1080/0960085X.2020.1857666.

Stentoft, J., Adsbøll Wickstrøm, K., Philipsen, K. and Haug, A. (2021), "Drivers and barriers for industry 4.0 readiness and practice: empirical evidence from small and medium-sized manufacturers", *Production Planning and Control*, Vol. 32 No. 10, pp. 811-828, doi: 10.1080/09537287.2020.1768318.

Teece, D.J. (2018), "Business models and dynamic capabilities", *Long Range Planning*, Vol. 51 No. 1, pp. 40-49, doi: 10.1016/j.lrp.2017.06.007.

Torres da Rocha, A.B., Borges de Oliveira, K., Espuny, M., Salvador da Motta Reis, J. and Oliveira, O.J. (2022), "Business transformation through sustainability based on Industry 4.0", *Heliyon*, Vol. 8 No. 8, p. e10015, doi: 10.1016/j.heliyon.2022.e10015.

Tortorella, G.L., Giglio, R. and van Dun, D.H. (2019), "Industry 4.0 adoption as a moderator of the impact of lean production practices on operational performance improvement", *International Journal of Operations and Production Management*, Vol. 39 Nos 6-8, pp. 860-886, doi: 10.1108/IJOPM-01-2019-0005.

Tortorella, G.L., Fogliatto, F.S., Espôsto, K.F., Vergara, A.M.C., Vassolo, R., Mendoza, D.T. and Narayanamurthy, G. (2020), "Effects of contingencies on healthcare 4.0 technologies adoption and barriers in emerging economies", *Technological Forecasting and Social Change*, Vol. 156, p. 120048, doi: 10.1016/j.techfore.2020.120048.

Tortorella, G.L., Narayanamurthy, G., Sunder M, V. and Cauchick-Miguel, P.A. (2021a), "Operations management teaching practices and information technologies adoption in emerging economies during COVID-19 outbreak", *Technological Forecasting and Social Change*, Vol. 171, p. 120996, doi: 10.1016/j.techfore.2021.120996.

Tortorella, G., Miorando, R., Caiado, R., Nascimento, D. and Portioli Staudacher, A. (2021b), "The mediating effect of employees' involvement on the relationship between Industry 4.0 and operational performance improvement", *Total Quality Management and Business Excellence*, Vol. 32 Nos 1-2, pp. 119-133, doi: 10.1080/14783363.2018.1532789.

Van Griethuijsen, R.A.L.F., Van Eijck, M.W., Haste, H., Den Brok, P.J., Skinner, N.C., Mansour, N., Savran Gencer, A. and BouJaoude, S. (2015), "Global patterns in students' views of science and interest in science", *Research in Science Education*, Vol. 45 No. 4, pp. 581-603, doi: 10.1007/s11165-014-9438-6.

Vera, D. and Crossan, M. (2004), "Strategic leadership and organizational learning", *Academy of Management Review*, Vol. 29 No. 2, pp. 222-240, doi: 10.2307/20159030.

Verhovnik, J. and Duh, E.S. (2021), "The importance of industry 4.0 and digital transformation for SMEs", *Elektrotehniski Vestnik*, Vol. 88 No. 3, pp. 147-149.

Vial, G. (2019), "Understanding digital transformation: a review and a research agenda", *The Journal of Strategic Information Systems*, Vol. 28 No. 2, pp. 118-144, doi: 10.1016/j.jsis.2019.01.003.

Zach (2021), "The complete guide: how to check MANOVA assumptions", Statology, available at: www.statology.org/manova-assumptions/ (accessed 2 April 2025).

Zangiacomi, A., Pessot, E., Fornasiero, R., Bertetti, M. and Sacco, M. (2020), "Moving towards digitalization: a multiple case study in manufacturing", *Production Planning and Control*, Vol. 31 Nos 2-3, pp. 143-157, doi: 10.1080/09537287.2019.1631468.

Zheng, T., Ardolino, M., Bacchetti, A. and Perona, M. (2021), "The applications of industry 4.0 technologies in manufacturing context: a systematic literature review", *International Journal of Production Research*, Vol. 59 No. 6, pp. 1922-1954, doi: 10.1080/00207543.2020.1824085.

Zheng, T., Ardolino, M., Bacchetti, A. and Perona, M. (2023), "The road towards industry 4.0: a comparative study of the state-of-the-art in the Italian manufacturing industry", *Benchmarking: An International Journal*, Vol. 30 No. 1, pp. 307-332, doi: 10.1108/BIJ-01-2021-0056.

Zheng, T., Ardolino, M., Bacchetti, A., Perona, M. and Zanardini, M. (2020), "The impacts of industry 4.0: a descriptive survey in the Italian manufacturing sector", *Journal of Manufacturing Technology Management*, Vol. 31 No. 5, pp. 1085-1115, doi: 10.1108/JMTM-08-2018-0269.

Further reading

Camiña, E., Díaz-Chao, Á. and Torrent-Sellens, J. (2020), "Automation technologies: long-term effects for Spanish industrial firms", *Technological Forecasting and Social Change*, Vol. 151, p. 119828, doi: 10.1016/j.techfore.2019.119828.

European Union (2003), "Commission recommendation of 6 may 2003 concerning the definition of micro, small and medium-sized enterprises (text with EEA relevance) [notified under document number C(2003) 1422]", *Official Journal of the European Union*, Vol. 124, pp. 36-41.

Jang, S., Chung, Y. and Son, H. (2022), "Are smart manufacturing systems beneficial for all SMEs? Evidence from Korea", *Management Decision*, Vol. 60 No. 6, pp. 1719-1743, doi: 10.1108/MD-12-2020-1632.

Kumar, G., Bakshi, A., Khandelwal, A., Panchal, A. and Soni, U. (2022), "Analyzing industry 4.0 implementation barriers in Indian SMEs", *Journal of Industrial Integration and Management*, Vol. 7 No. 1, pp. 153-169, doi: 10.1142/S2424862221500020.

Stornelli, A., Ozcan, S. and Simms, C. (2021), "Advanced manufacturing technology adoption and innovation: a systematic literature review on barriers, enablers, and innovation types", *Research Policy*, Vol. 50 No. 6, p. 104229, doi: 10.1016/j.respol.2021.104229.

Corresponding author
Pirjo Yli-Viitala can be contacted at: pirjo.yli-viitala@uwasa.fi