Employee Participation, Digital Sophistication and Innovation Performance: Analysis Based on the Finnish MEADOW Survey

Tuomo Alasoini
Kirsikka Selander

Abstract

The results of the Finnish MEADOW survey of 2021–2022, comprising responses of management from 1,106 companies, show that nearly half of Finnish companies employing ten or more people had produced a new or significantly improved product or service during the last two years. Of these companies, almost half had produced products or services new also to the market. Both the level of digital sophistication and the extent of employee participation in development are positively associated with the company's innovation performance after all other factors in the multinominal regression analysis are controlled. The odds ratios in the regression models are higher for innovations new to the market than innovations new only for the company. Broad employee participation shows the highest odds ratios of all variables included in the regression models for both types of innovation. As also companies' cooperation networks and customer involvement can play a role in innovations, we analysed the combined effect of the above four factors on innovation. A clear positive combined effect for both innovations new to the market and new only for the company was detected, suggesting that it is difficult for companies to build innovation superiority based on technological ability alone – or any other single factor – and that broad employee participation in development is an essential part of the portrait of an innovative company also in the digital age.

Keywords: Data analytics, digitalisation, innovation, participation

Introduction

Innovations are important for companies to achieve a competitive advantage in the market. In advanced industrial nations, innovations are needed to create the conditions for economic growth and, especially in the long run, for economic renewal and meeting the new challenges arising from the digital and green transitions. Innovation research has long been characterised by an emphasis on the importance of advances in natural and engineering sciences and the resulting technological innovations. However, in recent years, this view has been increasingly challenged in innovation research, giving more emphasis on the role of social and other non-technological innovations alongside technological innovations. The ways of producing innovations also have diversified as the economies of advanced industrial nations have become more information- and service-intensive and the education level of their population has risen. The role of companies' customers, users of their products and services, and their employees in innovation has become more important and at the same time an increasingly interesting object of research.

There are different types of innovation. Innovations can target, for example, products, services, operational processes, business models, sales and marketing strategies, organisational forms or management. The novelty value of innovations ranges from incremental reforms to radical and even revolutionary changes that disrupt accustomed rules and earnings logics in the market (e.g., Fagerberg et al., 2005; Tidd & Bessant, 2018). The diversity of innovations and the resulting incommensurability make it difficult to comprehensively compare the innovation performance of companies. Most often, the object of comparative company-level innovation research has been innovations in products and services, as also in this paper.

This paper examines the factors associated with the activity of Finnish companies to produce product and service innovations. We focus on both companies that have produced new products or services for the market during the last two years and those that have only produced new products or services for the company itself, and how both groups differ from companies that have not produced any kinds of product or service innovations. We are particularly interested in the significance of the level of companies' digital sophistication and that of employee participation for differences in companies' innovation performance and how and to what extent digital sophistication and employee participation are linked to each other. Our research interest stems from recent discussions on the deepening of digital divides between companies in productivity research (Andrews et al., 2016) and of people in communications research (Ragnedda & Muschert, 2018) and the economic and social implications of the divides, as well as studies on the impact of high-involvement work practices on organisational performance in management and organisation research (e.g., Wood, 2020). As data, we use the Finnish MEADOW employer survey funded by the WORK2030 programme (2019–2023), conducted as part of the government programme of Prime Minister Marin.

The next section includes a review on previous literature, with a focus on the role of digitalisation and employee involvement in innovation. This is followed by a description of the data, variables and methods. Thereafter, the results are presented. Finally, the results and limitations of the study are discussed, and conclusions are drawn.

Review of the literature

In today's innovation research, two modes of innovation are distinguished. The first of these – the STI-mode of innovation (STI = science, technology, innovation) – is based on the advancement made in science and technology. The second mode is based on learning by doing, using and interacting, called the DUI-mode of innovation (DUI = doing, using, interacting). Here, learning is typically based on the company's own experiences, feedback received from customers on the use of the company's products and services, or other ideas received from different partners in the company's business or innovation networks (Jensen et al., 2007; Parrilli & Heras, 2016).

Companies rarely innovate in isolation. The company's cooperation networks are already definitionally important in the DUI-mode of innovation. On the other hand, cooperation networks are also important in science- and technology-based (STI) innovations (Powell & Grodal, 2005). Many of these innovations require combining different scientific and technological knowledge, and an individual company often does not have sufficient special expertise in all the necessary areas. In practice, the difference between the STI-mode and DUI-mode is a sliding one, and the two modes often appear in a mixed form in real life.

The role of employees is especially important in the DUI-mode of innovation. While the STI-mode relies heavily on the utilisation and elaboration of explicit and global knowledge, the DUI-mode emphasises the role of locally embedded tacit knowledge, often attached to team-based and learning-oriented forms of work organisation. Such a view that stems from innovation research (e.g., Jensen et al., 2007) has a close connection to discussions in management, organisation and working life studies about the significance of the role of employees in companies' innovation and development activities. The discussions have taken place under such concepts as "high-commitment management" (Walton, 1985), "high-involvement management" (Lawler, 1986), "lean production" (Womack et al., 1990), "high-involvement innovation" (Bessant, 2003), "employee-driven innovation" (Høyrup et al., 2012), "practice-based innovation" (Melkas & Harmaakorpi, 2012) or "workplace innovation" (Oeij et al., 2017; 2023). All concepts emphasise – albeit from somewhat different perspectives – the communal nature of the creation of innovations and the importance of employee participation opportunities.

Digitalisation is currently one of the most important – if not the most important – force of change affecting the business operations of companies. The digital transition affects all industries and all types of companies in one form or another and at varying speeds. It can be assumed that the centrality of a company's position in the digital transition of its own industry or market is positively associated with a company's activity to develop new products and services (e.g., OECD, 2017). This can be assumed to also affect the role of employees in innovation within companies.

In the 2010s, the debate about the effects of digitalisation on work and employment was dominated by arguments about the massive job-displacing effects of technological development (e.g., Brynjolfsson & McAfee, 2014; Ford, 2015; Frey & Osborne, 2017; Schwab, 2016; Susskind, 2020). In these views, the effects of digitalisation on jobs, employment and work contents were often unilaterally derived from – realised or anticipated – advances in digital technologies. At the same time, the role of economic, social, cultural and institutional conditions that shape the actual changes in working life had a weaker footing in such analyses. In the view about the omnipotence of new technologies is nothing new. Technocentric concepts have dominated both public discussion and business management thinking also in connection with previous technological upheavals in history, as, for example, Kopp and his associates (2016) aptly present in their critical essay of the German-origin Industry 4.0 concept. Following their line of argumentation, digitalisation changes the landscape in which companies innovate, but does not displace employees or their knowledge and skills as unnecessary for innovation (see also Govers & Van Amelsvoort, 2019; Totterdill, 2017). The kind of role employees play in renewed work contexts is not so much technologically determined than socially constructed or shaped, reflecting managerial considerations, industry and workplace cultures and power relations between management and labour (e.g., Briken et al., 2017; Zuboff, 1988). To form a realistic picture of the impact of digitalisation on employees' role in innovation in digitalised environments, targeted empirical studies that help to understand both the specific technological and *non*-technological mechanisms characteristic of different industry and workplace contexts are needed.

Jensen and his associates (2007) highlight an inherent tension between the STI-mode and DUI-mode in company operations. The tension is seen in the need to reconcile knowledge management strategies based on the utilisation of codified knowledge with strategies emphasising the role played by informal communication and the mobilisation of tacit knowledge for problem-solving and learning. A special challenge for companies is combining these two modes and developing practices to promote their mutual complementarity.

This tension and challenge form the starting point for this paper's question setting. We ask to what extent the level of digital sophistication alone differentiates companies in terms of innovation performance, and to what extent the level of employee participation in development, customer involvement and companies' cooperation networks strengthen the disparities while controlling different company-level background factors. The research material does not allow us to study the differences separately for the STI-mode and DUI-mode of innovations. However, we assume that the importance of DUI-type features, and thus the participation of employees, is highlighted more in innovations new only for the company itself than in innovations new also for the market. The assumption is based on the fact that the importance of local knowledge is emphasised in the DUI-mode of innovation, whereas the STI-mode is more based on global knowledge, including advances in technologies.

Research methods and data collection

The data

The paper analyses the data obtained from the Finnish MEADOW employer survey, using the methodology developed in the European MEADOW project in 2008–2009 (The MEADOW Consortium, 2010). The guiding idea in MEADOW is to collect part of the data from employer representatives and part from employees working in the same organisations. Here, we will focus on the employer survey, but as we also make references to results of the employee survey, both surveys are described below.

Statistics Finland and Finnish Institute of Occupational Health conducted the employer survey as a stratified sample in terms of industry and organisation size. Based on the information from the Business and Place of Business Register of Statistics Finland, companies and public entities employing at least 10 people were selected for the target population, of which we will limit ourselves to companies in this paper. Data collection was carried out as a web survey between October 2021 and January 2022. Those for whom an e-mail address was available were primarily approached by e-mail. For those who had mail address but no e-mail address, a letter containing instructions for answering the web survey was sent. Finally, those for whom neither was available were contacted by telephone. The respondent was a person in charge of the organisation, such as the owner, managing director, or financial or human resources director, who would be best able to answer questions about the company. Several reminder messages about the survey were sent by e-mail and in paper form, and telephone interviews were also used.

The survey was sent to a total of 3,376 companies, of which 1,106 responded (response rate 33). The response rate varied by industry and by the size of the company. Response activity was highest in large companies employing at least 250 people, while it was clearly lower in small companies with less than 50 employees. There were also differences in response rates between industries. The bias caused by the loss of responses was corrected with the help of weighting coefficients, so the results can be generalised to Finnish companies with at least 10 employees.

In the second phase, between March and June 2022, an employee survey was carried out. From the organisations that had responded to the employer survey, a sample of four to eight people was taken, to whom the online survey was sent. The survey was sent to 5,110 employees working in companies, of which 1,263 responded (response rate 25). The most active response was among women, university graduates and older workers. Among industries, the response rates were highest and lowest in the same industries as in the employer survey, which causes a double bias in the data. The loss of employee data was also corrected with the help of survey weights, so the results can be generalised to employees working in the companies that participated in the employer survey – not to all Finnish private-sector employees.

The variables

We use the following variables obtained from the employer survey in the analyses:

Innovation performance. We asked the management whether the company had developed a new or significantly improved product or service during the last two years (yes/no). In addition, from those who announced that they had developed such a product or service, it was further asked whether any of these products or services were completely new to the market (yes/no). With the help of these questions, we formed a variable that divided the companies into three categories: those that had not developed new products or services (48%), those that had developed a new or improved product or service only for the company itself (28%) and those that had developed a new product or service for the market (23%).

Digital sophistication. The versatility of using data analytics was used as an indicator of the company's digital sophistication. The ability to compile, model and analyse various data in development and decision-making can be considered a key distinguishing feature of companies' level of technological sophistication in the digital transition (e.g., Lehrer et al., 2018). We first asked the management whether the company uses data analytics (yes/no). Those who answered positively were further asked whether it is used to a) develop the production or service process, b) increase customer satisfaction, c) develop work content, d) monitor work performance or e) improve employee well-being or occupational safety (yes/no). A sum variable was formed from the answers, which received values from zero to five according to the number of application areas. More than half of the companies did not use data analytics at all, but those that did mostly applied it for more than two purposes. For the analysis, the companies were split into three groups. The first group included those that do not use data analytics (56%). The rest were divided between those that use data analytics for one to four purposes (22%) and those that use it for all the five purposes (22%).

Employee participation. Employee participation was measured using two questions. At first, the management was asked whether, in addition to management, the staff regularly participate in groups or tasks related to operational development (yes/no). Those who answered positively were further asked about the percentage of participating personnel. For the analysis, the companies were split into three roughly equally sized groups: those where non-managerial personnel do not participate at all (35%), those were less than 30% of personnel participate (32%) and those where 30% or more of personnel regularly participate in operational development (33%).

Networking. We examined the versatility of companies' cooperation networks by asking whether the companies had used (yes/no) eight different types of ways to acquire expertise for the development of their operations during the last two years. The subjects of the questions were a) other companies in the industry, b) other companies in the value or production chain, c) consultants, d) universities, e) other educational institutions, f) authorities, g) labour market or entrepreneur organisations or h) new expertise is obtained from acquisitions or recruitment. A sum variable was formed from the answers, which received values from zero to eight (mean=3.40, sd=2.09). There were 9% of all companies that did not mention a single partner or a way to acquire expertise from the outside. At least five of the eight items were answered positively by 28% of the companies.

Customer involvement. We asked the management whether customers participate in the design or development of the company's products or services. The answer options and response distributions to them were: "regularly" (15%), "sometimes" (47%), "hardly at all" (24%) and "not at all" (14%). For the analysis, the two last categories were combined into one.

The following variables were used as control measures in the analysis:

Company size. The companies were divided according to the number of employees into three groups: small (less than 50 employees), medium-sized (50–249 employees) and large (at least 250 employees) enterprises.

Industry. Using the international Standard Industry Classification (TOL 2008 in Finland) and combining some categories with each other, the companies were divided into eight groups. After the mergers, the size of the groups varied from 78 (business services) to 413 (industry and infrastructure maintenance) companies.

Export share. The company's export share was measured by the management's estimate of how much turnover had come from sales outside of Finland in the last two years. The companies were divided into exporting companies and those operating only domestically. We also used non-responses (n=278) as a separate category in the analysis to avoid a drop of sample size in the multivariate logistic analysis.

Staff structure. The employer survey did not include a question about the company's staff structure. The staff structure was estimated with the help of Statistics Finland's register material, which contains information on the entire company's payroll and working hours. We classified the companies into two groups according to their average salary calculated per working hour and assumed that the size of the average salary is connected to the share of employees working as managers or professionals. Those whose average salary level was above the mean were classified as professional-dominated companies and the rest as non-professional-dominated companies.

The data analysis

At first, we investigated the connections between individual variables and companies' innovation performance using descriptive methods and cross-tabulations. We tested differences between groups using the chi-square (χ^2) goodness-of-fit test. In evaluating the differences between classes, we used row percentages and standardised residuals calculated from cross-tabulations.

After this, we combined the individual examinations by building two multinomial logistic regression models. Companies that had not produced new products and services in the last two years were set as the reference group. They were compared to companies that a) had introduced a new product or service to the market and b) that had only produced a new product or service for themselves. No weight coefficients were used in the multinomial regression models, as the variables used to form the weights are part of the model.

Finally, we used two multinomial regression models to investigate the combined effects of the level of digital sophistication, employee participation, networking and customer involvement on companies' innovation performance. The formation of the variables is described in the results section.

The results

The innovation performance of companies is associated with many background variables (Table 1). Among large companies, the proportion of firms that had produced product or service innovations both for the market and only for the company itself is higher than in small and medium-sized companies. There are also significant differences between industries. In the software industry and ICT services, the shares of companies that had produced innovations both new to the market (44%) and new only for the company (41%) are higher than in all other industries. The other extreme is represented by construction, where the respective shares are 8% and 16%. The company's staff structure is connected to the company's innovation performance. The companies, where a larger than average number of employees work in various expert positions, are ahead of the others, especially in their activity to produce innovations new to the market. Moreover, exporting companies are more active innovators than companies operating only in the domestic market.

Table 1: Innovation performance according to background variables: direct distributions (weighted figures).

		No product or service innovation	Product or service innovation new only to the company	Product or service innovation new to the market
Size of company (x^2=196.29, p<0.001)	Small	50%	29%	22%
	Medium-sized	45%	25%	30%
	Large	31%	34%	36%
Industry (x^2=2428.05, p<0.001)	Manufacturing	39%	31%	29%
	Construction	76%	16%	8%
	Trade, accommodation and catering	44%	38%	18%
	Business services	42%	31%	27%
	Education, health care and welfare	36%	26%	37%

	Transport and communication	68%	18%	14%
	Finance, insurance and real estate	58%	23%	19%
	Software and ICT services	15%	41%	44%
Staff structure (x^2=829.51, p<0.001)	Professional-dominated	57%	27%	16%
	Non-professional-dominated	37%	33%	31%
Export share (x^2=763.96, p<0.001)	Domestic market	56%	26%	19%
	Exporting	35%	35%	30%
	Information missing	42%	27%	31%
Digital sophistication (x^2=1399.36, p<0.001)	No data analytics	59%	25%	16%
	Data analytics for few purposes	35%	37%	28%
	Data analytics extensively	35%	29%	37%
Employee participation (x^2=1540.82, p<0.001)	None	64%	22%	14%
	Less than 30% of personnel	42%	36%	22%
	30% or more of personnel	36%	29%	35%
Customer involvement (x^2=1112.79, p<0.001)	Hardly/not at all	62%	25%	14%
	Sometimes	40%	32%	28%
	Regularly	37%	29%	34%
Networking (x^2=2106.62, p<0.001)	No external partners	84%	13%	3%
	One external partner	48%	37%	15%
	Two external partners	57%	27%	16%
	Three external partners	46%	28%	26%
	Four external partners	42%	33%	25%
	Five external partners	40%	29%	32%
	Six external partners	44%	36%	20%
	Seven external partners	22%	28%	49%
	Eight external partners	23%	33%	44%

We continued the analysis with two multinomial logistic regression models, where we examine how different variables are associated with innovation performance, when the connections of other variables are controlled. Table 2 presents the results of the multinomial logistic regression analysis that differentiate companies in terms of innovation performance. The table shows odds ratios and their 95% confidence intervals. Odds ratio greater than one indicates that odds for the event is increasing, and less than one that odds is decreasing. The connection of variables to innovation performance is statistically significant, if the confidence interval does not include one.

Table 2: Variables associated with innovation performance based on multinomial logistic regression analysis, with the odds ratios and their 95% confidence intervals.

		Product or service innovation new only to the company	Product or service innovation new to the market
Size of company	ref.=Small	1	1
	Medium-sized	0.86 (0.57-1.27)	1.21 (0.81-1.82)
	Large	0.81 (0.46-1.39)	1.13 (0.65-1.99)
Industry	ref.=Software and ICT services	1	1
	Manufacturing	0.58 (0.31-1.09)	0.69 (0.36-1.32)
	Construction	0.24 (0.10-0.59)**	0.24 (0.10-0.61)**
	Trade, accommodation and catering	0.88 (0.41-1.89)	0.51 (0.22-1.16)
	Business services	0.37 (0.16-0.86)*	0.37 (0.16-0.89)*
	Education, health care and welfare	0.42 (0.15-1.21)	0.49 (0.16-1.52)
	Transport and communication	0.33 (0.15-0.73)**	0.33 (0.14-0.76)**
	Finance, insurance and real estate	0.24 (0.11-0.56)**	0.28 (0.12-0.65)**
Staff structure	ref.=Non-professional-dominated	1	1
	Professional-dominated	1.65 (1.14-2.40)**	1.88 (1.28-2.76)**
Export share	ref.=Export	1	1
	Domestic market	0.81 (0.53-1.24)	0.59 (0.38-0.92)*
	Missing information	0.97 (0.60-1.58)	1.15 (0.72-1.85)
Digital sophistication	ref.=No data analytics	1	1
	Data analytics for few purposes	1.13 (0.74-1.72)	1.15 (0.74-1.79)
	Data analytics extensively	1.71 (1.10-2.66)*	2.40 (1.53-3.78)***
Employee participation	ref.=None	1	1
	Less than 30% of personnel	1.82 (1.17-2.84)**	1.37 (0.85-2.20)
	30% or more of personnel	2.43 (1.51-3.91)***	2.56 (1.57-4.18)***
Customer involvement	Ref.=Hardly/not at all	1	1
	Sometimes	1.47 (0.99-2.18)	1.59 (0.92-2.74)
	Regularly	1.55 (0.92-2.60)	1.70 (1.11-2.60)*
Networking		1.17 (1.07-1.28)**	1.13 (1.03-1.25)*

Goodness of fit: deviance=1678.40, p=0.384, Pearson=1687.26, p=0.384. Pseudo R^2: McFadden=0.115, Nagelkerke = 0.249, Cox and Snell=0.221. *** p<0.001, ** p<0.01, * p<0.05.

Companies that use data analytics extensively have produced both types of innovation more often than companies that do not use data analytics at all. The odds ratio is higher for innovations new to the market. On the other hand, companies that use data analytics more narrowly do not statistically differ from non-users in either type of innovation.

The regular participation of personnel in development also has a positive association with the company's innovation performance. Here, again, the odds ratios are highest for those companies in which staff participation is most extensive. In fact, broad staff participation shows the highest odds ratios of all variables included in the models for both types of innovation.

The versality of company networks also has a statistically significant connection to both types of innovation. As the network diversifies, the company's opportunities to produce new innovations increase.

Customer involvement also is positively associated with innovation performance. However, the association is statistically significant only for innovations new to the market and in cases where customer involvement is regular.

Furthermore, most of the previously noted disparities in background variables persist even after controlling for other variables. The only exception is that small and large businesses no longer differ in terms of innovation performance.

The last part of the statistical analysis focuses on the combined effect of the four variables that were selected for the actual target of our study.

As Table 2 shows, extensive use of data analytics, regular and broad employee participation in development, regular customer involvement and versatile networking are all positively associated with the company’s innovation performance in one way or another. Next, we analyse how different combinations of these four factors affect the odds ratios for the two types of innovation separately. In order not to have too many combinations, we dichotomised each variable. The cut-off points were between companies that use data analytics extensively (for all five purposes) vs. others, companies where 30% or more of personnel participate regularly vs. others, companies where customers involve regularly vs. others, and companies that are networked with at least five of the eight partners vs. others. Based on the dichotomisation, 40% of companies remained below the cut-off point for all four variables. 32% were above the cut-off point for one variable, 20% for two variables and 8% for three or four variables. The four categories that were formed were mutually exclusive.

The positive combined effect between these four variables comes out clearly in the two multinomial logistic regression models, where the reference point was companies that did not exceed the cut-off point for any variable (Table 3). The odds ratios increase consistently depending on how many variables the company exceeds the cut-off point. The odds ratios are higher across the board for innovations new to the market than for innovations new only for the company itself.

Table 3. The odds ratios and confidential intervals of the combined effects of extensive use of data analytics, employee participation, networking and customer involvement on innovation performance: multinomial logistic regression models (company size, industry, staff structure and export share adjusted).

	Product or service innovation new only to the company	Product or service innovation new to the market
ref.=None	1	1
Extensive use of one factor	1.47 (0.98-2.20)	2.18 (1.40-3.40)**
Extensive use of two factors	2.54 (1.59-4.06)***	3.65 (2.21-6.03)***
Extensive use of three or four factors	5.55 (2.91-10.59)***	8.23 (4.25-15.95)***

Goodness of fit: deviance=672.24, p=0.002, Pearson=609.58, p=0.122. Pseudo R^2: McFadden=0.098, Nagelkerke = 0.216, Cox and Snell=0.192. *** p<0.001, ** p<0.01, * p<0.05.

Discussion and conclusions

In this paper, we were interested in the connection between the company's digital sophistication and its activity in producing product and service innovations. It has often been said that "data is the new oil" in the digital economy. For this reason, we measured the company's digital sophistication by how extensively it utilises data analytics in its operations. The results showed that extensive use of data analytics is positively related to innovation performance when the effect of all other factors in the multinomial logistic regression analysis was taken into account. Our original assumption was therefore clearly supported.

OECD researchers have found that differences in the productivity of companies in industrial countries have grown in recent years. They suggest that divergence in measured multi-factor productivity may reflect technological divergence between companies (Andrews et al., 2016). In the MEADOW survey, in addition to the current use of data analytics, we also asked the management companies' intentions to expand the use of data analytics in the future. There was a clear positive correlation between current use and the intent to increase the use of data analytics, indicating that the digital divide between companies in Finland is still widening rather than narrowing (Alasoini et al., 2023). The widening digital divide threatens to further exacerbate difference in innovation performance and, in this way, opportunities for productivity growth between companies. Growing differences in productivity can still have negative labour and social consequences in the form of, among other things, growing wage differences and other increasing inequalities in working conditions and terms of employment.

Another key area of interest in our paper was the significance of employee participation for the company's innovation performance. The extent of employee participation in development activities had an independent positive connection after all other factors were controlled, both to innovations new to the market and to innovations new only for the company itself. Our original assumption was that employees' participation would have played a more important role in innovations new only for the company itself. However, contrary to our expectations, the odds ratio was higher in the case of innovations new to the market. Our cut-off point for "broad" employee participation was relatively low (30% or more of staff participate regularly). We also did the analysis using 50% as a cut-off point for "broad" employee participation without this having significant effects on the results.

Our original assumption was based on the view of the similar role of the local knowledge of the company's customers, users of their products and services, and personnel, especially in DUI-type of innovations. However, Kesting and Ulhøi (2010) claim that innovations that can be considered employee-driven are often more radical than user-driven innovations. The authors' argument is not based on empirical research, but on their theoretical framework and a number of anecdotal examples. In any case, our results can be considered in line with the authors' claim. In the multinominal regression model, the odds ratio of broad and regular employee participation in innovations new to the market was clearly higher than that of regular customer involvement, suggesting a more prominent role for employee participation compared to customer involvement in radical (new-to-the-market) product and service innovations.

It is possible to give different theoretical interpretations to the observation of the positive connection of broad and regular employee participation to innovation performance (cf. Wood, 2009, pp.66–67). One possible interpretation is that participation in itself helps companies produce more product and service innovations. Another, more cautious interpretation is that broad and regular participation of personnel does not necessarily have direct and demonstrable effects on innovation performance as such, but broad and regular participation rather reflects an inclusive and high-trust company management style, which can have positive effects on innovation performance through *many* different mechanisms, such as increased personnel initiative, information sharing and dialogue between management and personnel. Our data do not allow us to give a definite answer to this issue, but intuitively we consider the latter explanation to be more realistic.

In addition to the fact that broad and regular employee participation in development can be considered an indicator of high trust between management and personnel, high trust in itself can also have a positive connection with the company's innovation performance. This view is supported by the MEADOW employee survey, in which employees were asked about their view on the outcomes of their participation in development activities. The results showed that in high-trust companies, employees not only participated more actively in development, but also saw the benefits of participation clearly more positively than others, regarding both improvements in products, services and operations as well as employee work well-being (Alasoini et al., 2023). Without trust, employees' participation in development may have rather negative than positive consequences for the organisation. Participation without trust and perceived opportunities to influence can increase employees' workload, frustration and cynicism, as well as tensions and conflicts within the organisation, leading to a weakening of cooperation and even a decrease in productivity. The phenomenon is already familiar from previous industrial relations literature (e.g., Fox, 1974).

Finally, in our paper we were also interested in how and to what extent the level of employee participation in development strengthens the effect of the level of digital sophistication on innovation performance. As, according to innovation research, also companies' cooperation networks and customer involvement can play a role in both STI- and DUI-type of innovations, we included both in the analyses in which we examined how different combinations of these factors affect companies' innovation performance. A clear positive combined effect for both innovations new to the market and new only for the company was detected. The results suggest that, even in the digital age, it is difficult for companies to build innovation superiority based on their technological capability alone – or any other single factor. The ability to produce innovations is the sum of many intertwining factors. Our results show that broad employee participation in development is an essential and perhaps even inevitable part of the portrait of an innovative company. Future research with longitudinal study design is needed to make more confident conclusions about causality.

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About the authors

Tuomo Alasoini is Research Professor at Finnish Institute of Occupational Health (FIOH) and Adjunct Professor of Sociology at the University of Helsinki. Before moving into FIOH, he worked for the Committee for Labour Relations, the Ministry of Labour and Finnish Funding Agency for Innovation Tekes in various management and expert tasks. Alasoini has PhD in sociology (1990) and industrial engineering and management (2016). During his work career, he has participated in many European research and development activities, including WORK-IN-NET (2004–09), European Workplace Innovation Network EUWIN (2013–16) and the Nordic "Future of Work" project (2017–20).

Kirsikka Selander is Special Researcher at Finnish Institute of Occupational Health (FIOH). She has PhD in sociology (2018) from the University of Jyväskylä. In recent years, in addition to the Finnish MEADOW survey, her research has mainly focused on the well-being of social and health care employees.