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A method for anticipating the disruptive nature of digitalization in the machine-building industry

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ABSTRACT

The purpose of this paper is to create a technology foresight method in which the visual analogue scale is used to harness the wisdom of expert crowds, namely, industry experts, in anticipating potential disruptions in an industry. In an empirical demonstration, we investigate experts' views and perceptions of possible future disruption caused by digitalization in an established machine-building industry. We demonstrate the usability of the proposed method in detecting future worldviews of experts grouped by their position in the value chain. The results show polarized responses, with considerable clustering among groups. For example, respondents who were inclined to view digital technologies as disruptive (i.e., as changing the paradigm of value creation in machine-building) also viewed them as related more to service and business models than to products and operation. We discuss the theoretical and practical contributions of the proposed method and suggest fruitful avenues for future research.

1. Introduction

Disruptive innovation brings to an industry new performance parameters that existing products do not provide (Christensen, 1997), and disruptive innovations often promise lower prices. The offering of disrupters then contrasts with incumbent firms that provide performances that overshoot mass markets with expensive price tags. Disruption in an industry is also a process that comes about with new business models utilized by disrupters, thus shaking the positions of incumbents (Christensen et al., 2015). Disruptive innovation theory has been under close scrutiny in academic research [see further e.g. (King and Baatartogtokh, 2015; Markides, 2006; Yu and Hang, 2010)] while spreading widely to the practicing community (Nagy et al., 2016; Sampere et al., 2016).

The need to detect and anticipate disruptive innovations is the cornerstone of disruptive innovation (Christensen, 2006; Mäkinen and Dedehayir, 2014; Paap and Katz, 2004), and the normative purpose of disruptive innovation theory is to seek an understanding of why incumbents, in many cases with ample resources, fail to compete with smaller disrupters. The question of how to anticipate disruptive innovations has attracted much attention [see e.g. (Adner, 2002; Hüsig, 2009; Keller et al., 2008)] and various approaches have been proposed [see e.g. (Cheng et al., 2017; Dotsika and Watkins, 2017; Klenner et al., 2013; Momeni and Rost, 2016)] urging industry agents to exercise forward-looking searches and foresight activities. Moreover, there have recently been calls for more empirical research on these forward-looking search processes (Rohrbeck et al., 2015). However, to our knowledge, existing approaches have not attempted to use the wisdom of crowds (Bonabeau, 2009) for anticipation of disruptive changes in an industry with industry experts. Using industry experts has the potential to increase the accuracy of detection of change characteristics, because experts outperform crowds of non-experts (Budescu and Chen, 2014), and larger groups are more accurate than smaller groups (Mannes, 2009). Thus, part of this paper's contribution is a method for using industry experts to detect and anticipate disruptive changes.

The pressing need to anticipate disruptions is shared by all industries, but in mature industries, companies face considerable challenges (Sommarberg and Mäkinen, 2017). Traditional investment-heavy industries currently face potentially disruptive forces from technological advancements in multiple domains (Berggren et al., 2015). Incumbents in these industries are tied to existing value networks with established processes and practices (Macher and Richman, 2004). Furthermore, actors in different parts of the value chain have differing views on technological changes and how value is created (Stabell and Fjeldstad, 1998).

The machine-building industry, the context of the present paper, consists of three types of players:

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- firms (called *enablers*) that supply digital technologies, which can be products or services;
- machine-builders (called actors) that, integrate the technologies of external suppliers or their own technologies to build machines using several engineering disciplines;
- firms (called users) that use the machines in order to create value in an industrial process.

This classification follows a traditional value-chain approach (Porter, 1979). This approach is adopted in this study, because, ex ante, we expect to find similarities (and dissimilarities) between the groups above. Our expectations are based on the assumption that a practicing manager's perception whether something is disruptive or enables disruption depends on what type of investment decisions the manager deals with, and this in turn depends on the manager's position in the value chain (Lukas and Welling, 2014). Furthermore, machine-building is an established capital goods business-to-business industry that has established processes, value chains, means of competition, industrial networks, and company practices (Prahalad and Bettis, 1986; Spender, 1989).

Individual players in the existing industry value chain create discontinuities by means of research, development, and innovation activities. Mechanisms of those discontinuities are described, for example, in terms of trajectories (Dosi, 1982) or S-curves (Foster, 1986). However, the current players in the value chain are often capable only of sustaining continuous improvement or creating leaps for the existing learning curve (Macher and Richman, 2004), whereas out-of-industry players more often cause disruptions (Christensen, 1997; Hacklin et al., 2013).

In this paper, digitalization refers to the use of digital technologies to create value for a firm. Digital technologies are generic technologies (Dussage et al., 1992) owing to their application across products and industries. The disruptive potential of digitalization is familiar from examples such as Amazon (Chris and Isabelle, 2013). Porter and Heppelmann illustrated how digital technologies change the competitive arena from products to systems of systems in capital investment goods (Porter and Heppelman, 2014). Furthermore, the World Economic Forum forecasted the industrial internet's transformation of the products and services market in a performance-oriented direction, referred to as the outcome economy (World Economic Forum, 2015). Zysman et al. (2013) used the term "services with everything" to describe a similar transformation.

Digital transformation is complex and systemic when transactions shift from products to outcomes and simultaneously, platforms with complementors decouple established value chains (Gawer and Cusamo, 2002). This poses a question: if one could detect some of the changes ex ante, how should a firm integrate this understanding into its strategy and action plans? Minzberg et al. (1998) recommended learning as a key attribute in forming a strategy when development is inevitable, but the business environment is unpredictable and confusing. The same notion of learning with experiments is found in the start-up movement and the concept of minimum viable product (Ries, 2011). Thus, experiments and learning are critical in an uncertain business environment. We argue that ex-ante understanding of the nature of the transformation that digitalization enables is advantageous for a firm's strategy formation and for avoiding the traps of bounded rationality (Simon, 1979), availability heuristics (Tversky and Kahneman, 1973), or other aspects of management cognition that hinder managers from moving out of their comfort zone.

In this paper, we study the perception of this transformation in the current value chain of the machine-building industry. In our approach, we divide the alternative future path of industry change into three distinct concepts: *continuous improvement*, an incremental improvement as a result of a development activity (it is assumed that in competition, continuous improvement will ensure that a firm maintains its current position relative to its peers); *quantum leap* (a major change in the market position as a result of a development activity that typically is the result of a radical innovation); and *disruption* (a paradigm change in rules concerning how value is created in business).

2. Data and methods

Survey studies with detailed questions have worked well in numerous research projects, but such studies are laborious for respondents, which can lead to low response rates. For the same reason, in large organizations, senior business or staff executives often delegate the task of responding to those lower in the organization. To draw any meaningful conclusions based on statistical analysis in consumer business, one needs a large number of responses. In the business-to-business environment, researchers have traditionally been satisfied with smaller samples. This creates a serious limitation, which rests on an assumption that large organizations share unanimous views that can be expressed by single informants. It is less critical if the informant has to describe past or current affairs than if he or she has to judge future developments. This has already been recognized in customer satisfaction surveys, where methods such as the Net Promoter Index are based on simplicity (Leisen Pollack and Alexandrov, 2013). Ease of responding is an element of simplicity that increases the response rate. A visual analogue scale (VAS) makes it easier to express judgment on abstract matters, and such scales have been used widely in medical research where, for example, the patient has to describe the degree of pain he or she is experiencing (McCormack et al., 1988; Williamson and Hoggart, 2005). Information technology has also increased ease of responding by offering easy-to-use interfaces. Surveys were previously sent by ordinary mail; today, one receives a link to a survey by email. This method puts pressure on how to articulate the questions so that respondents understand them in the same way. It is particularly demanding if the research objective is a phenomenon that is emerging and a shared lexicon is missing. A link to a survey is also easy to forward, which lowers the barrier to delegating the task of responding to someone other than the person the researcher was targeting.

We investigate managers' perceptions of potential disruption with a survey method that utilizes novel measures based on a VAS, and we create novel visual representations of the results according to the disruptiveness of the respondents' views. The respondents in the survey were categorized according to two background factors: position in the value chain (*enablers*, *actors*, and *users*) and the role of the respondent in his or her organization, namely, managers in charge of development (*developers*) or business (*decision-makers*). There are two dependable factors: the perceived degree of impact of digitalization and the judgment as to the drivers that may cause it. Respondents who responded affirmatively that digitalization would cause disruption to the machine-building industry were also asked to judge the time it would take for the paradigm to change. Respondents were also asked how well their organization is prepared for digitalization in the context of their own perception of the potential impact. This last question can work as a dependable factor, but it can also partly explain responses concerning either of the dependable factors. The survey form is shown in Appendix 1.

The survey was conducted during eight seminars held between late 2015 and early 2016. The process was formatted so that definitions of the dependable factors were explained to the participants, who thereafter evaluated the concepts one by one with preset timings. This method attempted to mitigate the problem in surveys of respondents understanding the questions differently. The names of the respondents and their companies were known, which further validated their area of expertise for the research question, although this information was not attached to individual responses. The total number of respondents was 278, and 85% of them came from Northern European countries. The company lists for the seminars indicated that the majority of participants came from global companies; thus, cultural biases were likely to be combined with and influenced by the respondents' company cultures. Enablers were telecom, software, and information technology services companies, which meant that many work with consumer and industrial customers. Machine-builders are a relatively homogenous group, in the sense that they work globally with customers in contexts where their equipment is a critical asset. The largest user group was ports and terminals. Other large user segments were the mining and process industries. Titles in the attendee list revealed that the vast majority of the respondents were either senior business management personnel (Managing Director, Vice President, and director level) or senior research and development personnel (Chief Technology Officer, Chief Information Officer, Vice President, or director level).

Respondents first selected the category (continuous improvement, quantum leap, or disruption) for the digitalization impact and the drivers section. The strength of the chosen category was indicated by placing a cross ("x") on a continuous scale in which the leftmost point represented the weakest impact and the rightmost point the strongest. During the analysis, the three categories were divided into three sections, which translated the VAS values from 1 to 9, with 9 indicating an extreme disruption. The level of preparedness of the respondent's own organization was evaluated with a VAS ranging from -2 to $+2$, where $+2$ indicated the strongest confidence of being a winner relative to the peer group with the current level of investment in the presented digital technologies and related management concepts. In the analysis, the VAS was divided into three equal sections so that responses close to 0 were neutral, responses lower than -0.7 were regressive, and responses higher than $+0.7$ were progressive.

We used four attributes to select the emerging technologies in our empirical demonstration, following heuristic criteria of radical newness, relatively fast growth, expected impact, and uncertainty [outlined e.g. in (Rotolo et al., 2015)]. Many reports and accounts have studied the impact of various aspects of digital technologies on value creation (BCC Research, 2014; Bradley et al., 2013; LeHong et al., 2014; Manyika et al., 2013), and these could be used for searching and selecting appropriate survey items. The selection of technologies to be included was based on searching a number of research reports and articles, industry news accounts, etc., with the criteria outlined above, emphasizing the emerging nature of technologies in the machine-building industry. Finally, six technologies were selected to be included in the survey: 3D printing/additive manufacturing (3D or AM), big data/artificial intelligence (big data), cloud computing (cloud), the Internet of Things (IoT), model-based system engineering (MBSE), and robotics. Additionally, many reports highlighted management concepts linked to digital technologies, such as open innovation (OI) and the Industrial Internet (II), which were selected to represent a change in the operating environment. Both concepts were deliberately embedded within the six technologies in the survey to capture respondents' views on the importance of the concepts for the potential disruption vis-à-vis the six technologies. The dependent variables were four objects of the impact of digital technologies: products, services, operations, and business models. The descriptions of the dependable variables try to capture some of the potential disruptive nature that is embedded in those variables, as discussed below.

AM is a manufacturing technology whose disruption potential relates to products, services, operations, and business models. AM enables designs that were previously impossible and can enable manufacturing to be a new kind of service business or enable the printing of spare parts as a new type of manufacturing recipe-based business model. The main operational disruption is embedded in AM's potential to transform part of the supply chain into digital.

Big data and artificial intelligence (AI) relate to analytics, and they are linked to the speed, cost, and quality of sense-making (in this context, value creation in business). Machine intelligence is often compared to human cognition; that is, the key question whether the machine can learn to recognize images, make logical conclusions, or understand contexts. Big data and AI are often used together. Although they are not the same thing, they are related, and are therefore packaged as a single concept together with the notion of a leap in sense-making.

Cloud computing and its three service models—Infrastructure as a Service, Platform as a Service, and Software as a Service not only offer activity-based pricing and unlimited capacity even for small companies (Mell and Grance, 2011) but also enable new business models, such as Salesforce.com, in account management (Weinhardt et al., 2009).

The Internet of Things (IoT) is often grouped with the Industrial Internet. In this paper, IoT refers specifically to the phenomenon of connecting, monitoring, and controlling of a fleet of machines, individual machines, or components embedded in those machines. The impact of this phenomenon is close to the notion from the early 1980s of Metcalfe's law, which states that "the value of a network grows as the square of the number of its users grows" (Metcalfe, 2013).

The Industrial Internet (II) is considered to be a digital business model. In the machine-building context, II can be understood as harvesting data from an intelligent fleet of machines, processing that data into knowledge that is developed as a valuable algorithm (productivity, cost saving, safety, etc.), packaging it as a piece of software, and delivering it as a service where the value is shared between the developer and the user. This understanding was emphasized in the seminar introductions, as use of the II concept is diverse. General Electric has stated that the core aim of II is connecting intelligent machines, advanced analytics, and mobile people at work (Evans and Annunziata, 2012).

MBSE was evaluated specifically because of its relevance to machine-builders. MBSE needs software tools and processes to yield benefits. The power of MBSE is related to its ability to model existing knowledge, engage internal and external complementors to innovate and simulate around the model, and to combine different disciplines, such as mechanical, electrical, and software engineering.

Open innovation (OI), or one of its forms, crowd, is a business paradigm that also reflects behavioral change in developers. Chesbrough (2006) defined open innovation as "the use of purposive inflows and outflows of knowledge to accelerate internal innovation and expand markets for external use of innovation respectively." This definition implies that the OI method can be applied to a firm's products or services, internal operations (primary or support processes), or business models. Teece (2007) argued that there is a trap in OI if it is seen as an alternative to integrating the knowledge that exists among suppliers, customers, and complementors.

In this paper, robotics refers to work machines becoming autonomous and the impact of this development in various parts of the value chain. Some practitioners regard the intelligence element of robotization as solely a task of the upper system, but there are contrasting opinions about the level of intelligence necessary for an individual machine. In the seminar experiment, the focal point of robotization was the meaning of an industrial process becoming autonomous. Brynjolfsson and McAfee emphasized the contribution of human–robot co-operation to a more automated economy (Brynjolfsson and McAfee, 2012).

3. Results

The number of respondents in different parts of the value chain and functions in organizations is depicted in Table 1. The majority of the users were from ports and terminals.

Table 1
Participants in the survey.

Role/value chain	Enablers	Actors	Users
Developers	52	75	30
Decision-makers	23	75	23
Total	75	150	53

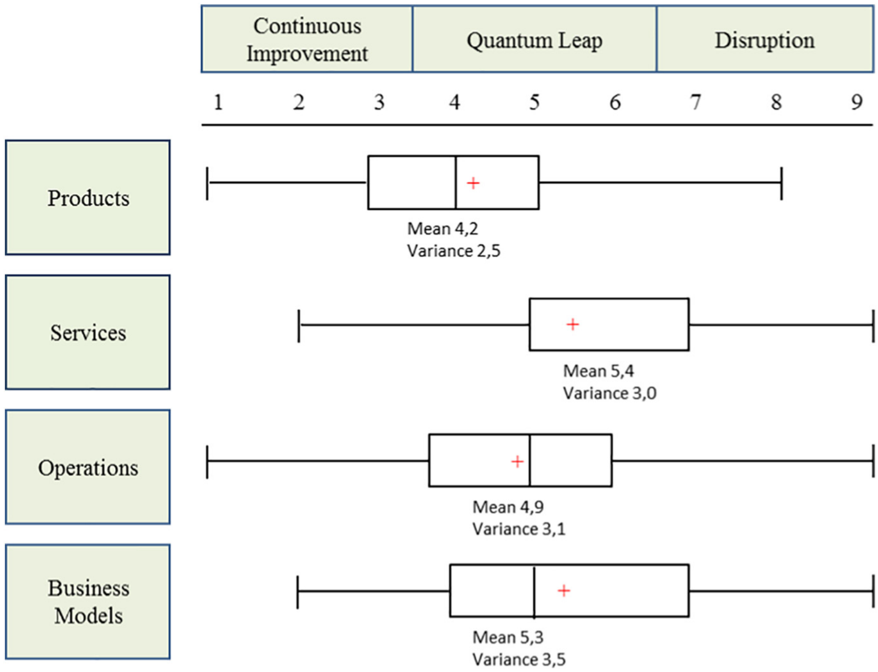


Fig. 1. Disruption impact by whole population, unbalanced data. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

The results of the Shapiro-Wilk test show that the data do not follow a normal distribution. Table 1 also reveals that the size of the sub-populations differed, which requires balancing in order to increase the generalization of the results. Each sub-population had three types of investment behavior (regressive, neutral, and progressive), which equals 18 sub-populations. The balancing is done by dividing the number of participants (278) by the number of sub-populations (18), which equals 15.45, the total weight of the sub-population. The coefficient for an individual sample is calculated by dividing the number of samples in the corresponding sub-population by the total weight of the sub-populations. In further analysis, these coefficients are used, except when it is specifically indicated that unbalanced data are used.

The first result is the systemic impact of digitalization (i.e., continuous improvement, quantum leap, and disruption). The results of the impact by object can be seen with the unbalanced data for the whole population in Fig. 1 and by the value chain with the balanced data in Fig. 2.

In the plots, the box contains 50% of all values. The vertical line in the box represents the median value, and the lines outside the box indicate the 95% confidence intervals. Individual points beyond those lines can be considered as outliers. The red plus sign (+) represents the average value of the sub-population view. Average and variance values have also been added in the figures. The results in Fig. 1 and Fig. 2 indicate the following:

- As the Shapiro-Wilk test indicated, the data do not follow the normal distribution.
- With both balanced and unbalanced data, products are perceived as having the least disruption impact.
- Digitalization is expected to have a quantum leap impact on operations, a view that is relatively similar in the value chain.
- Potential disruption is most likely to take place in the services and business models (although views regarding the business models had the highest variance).
- For all value chain members, the relative disruption impact by the object is the same.
- For all objects, users have the highest variance in their views.
- For all objects, enablers perceive digitalization as causing more disruption than actors and users.

The assumption is that digitalization has not yet caused industrial disruption in machine-building. The analysis based on the whole population suggested that digitalization offers major opportunities to shift firms' competitive positions. This does not necessarily imply industrial disruption. Therefore, the next analysis presents the views of respondents who judged the impact as either weak continuous improvement (i.e., a value of 2 or below) or strong disruption (8 or higher). This analysis attempts to increase the understanding of the potential dynamics in the value chain. The results are presented in Fig. 3.

The analysis of the stronger views does not change the previous conclusion concerning the relevance of services and business models. However, users held that view more strongly, and it was coupled with their strong judgment that disruption is not product-related. This difference might contain a clear business relevance, despite the high degree of polarization of users' views.

The primary objective of the enquiry was not to forecast the timing but to judge roughly how the participants viewed the potential impact. The timing questions were included so that respondents who viewed digitalization as having a disruptive impact on any of the objects also gave their judgement on the timing of that impact. Disruptive status was defined as the point at which a new digitally enabled way to create value had become an industry norm. The categories were less than 5 years, between 5 and 10 years, and more than 10 years. The results are shown in Fig. 4, which represents the relative shares of the timing for each object.

The first analysis suggested that digital disruption in machine-building is least likely via products. However, if a firm can do it, the introduction time appears to be shortest in this area. Likewise, changing an industry's business model has a high disruption opportunity but also the longest lead time. Changing the operation in this respect falls in between the two extremes. Services have almost as short a transformation time as products, but the high disruption potential makes them the most attractive choice from the business perspective.

We further investigated the disruptiveness of the eight key concepts, and we report the results in Fig. 5 and Fig. 6.

The main observations from these plots are as follows:

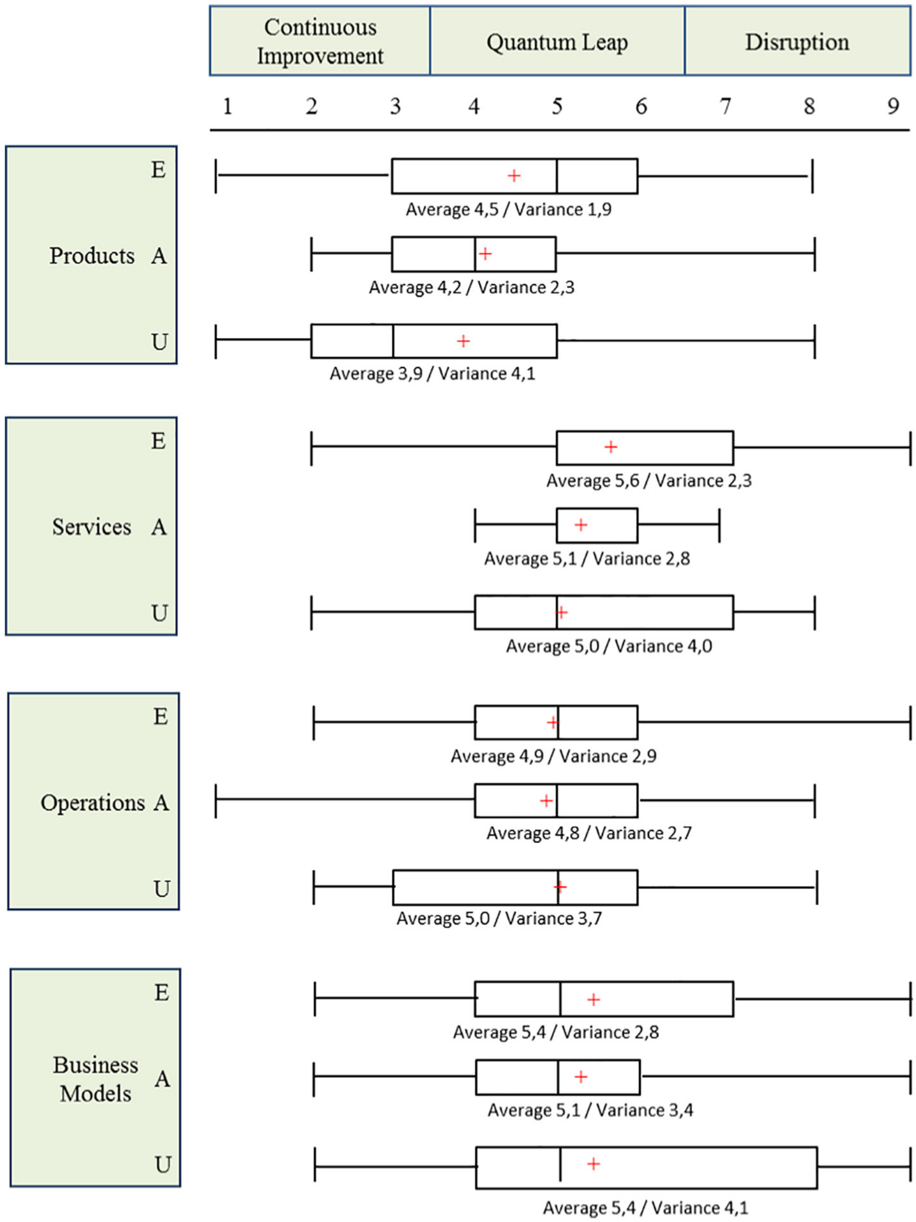


Fig. 2. Disruption impact by value chain, balanced data. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

- Variances in the drivers are higher than variances in the objects; variances are particularly high in 3D printing and robotics.
- Enablers emphasize data-centric disruption more than users and actors.
- Users see more disruptive potential in 3D printing and robotics than enablers or actors.
- II and OI, which are business concepts enabled by digital technologies, attract generally higher average values than technological drivers.

Fig. 7 illustrates the weak continuous improvement (2 or below) or strong disruption (8 or higher) views of the respondents in relation to the drivers. There was a more balanced range of views for disruptive objects than for drivers. For drivers, there were far more perceptions of weak continuous improvement than strong disruption. The explanation for this could be that the respondents believe that digitalization has a systemic impact, even if they did not highlight any of the individual technologies that drive digitalization. The range of views was more balanced for II and OI. It is also notable that users' perceived 3D printing and robotics as more disruptive than data-centric technologies.

The last perspective deals with actions. The respondents were asked to judge how adequate their digitalization investment was in relation to its perceived relevance; that is, the more disruptive the respondent sees the impact as, the more investment is needed to overperform peers. In the analysis, the VAS was categorized into regressive, neutral, and progressive responses, which are presented in Fig. 8. Enablers judged digitalization as having the strongest disruption impact, but they also believed more than actors and users that their investment was likely to make them winners (41%). The actors' responses indicated that, as a group, they followed a normal distribution, where majority of firms are making similar investments. The group of users was more polarized into winners and losers.

4. Discussion and conclusions

In this paper, we investigated a survey methodology that combined

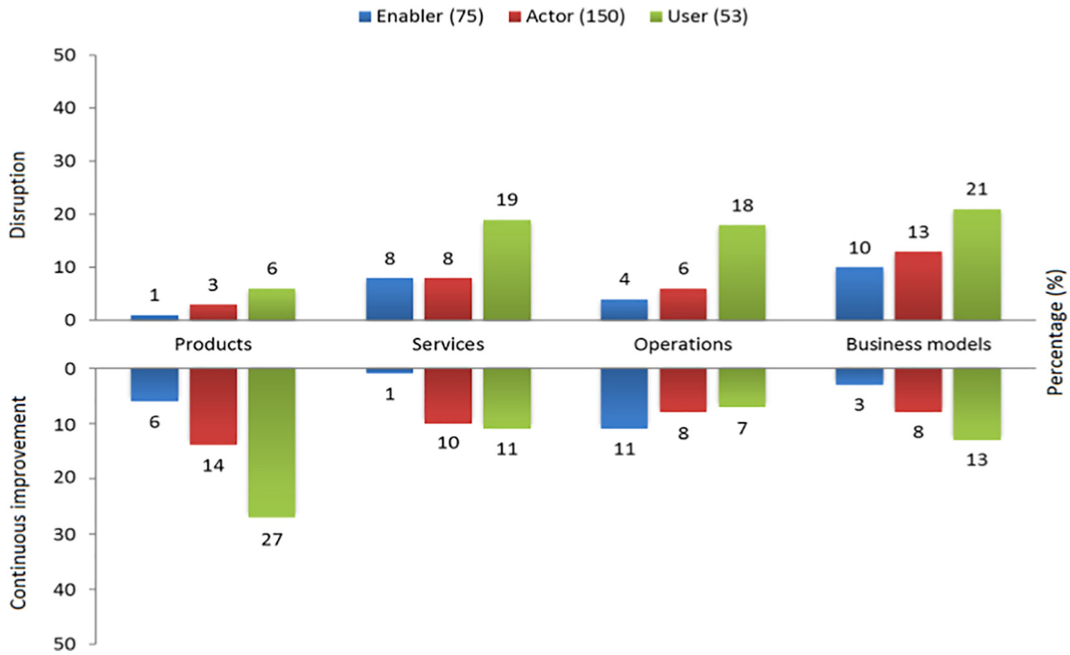


Fig. 3. Weak and strong disruption impacts by value chain, balanced data.

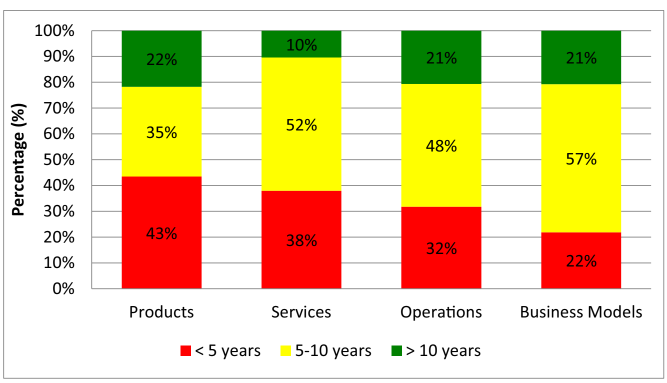


Fig. 4. Timing of the potential disruption (whole population, unbalanced data).

visual input (a VAS), seminar-based sampling, and presentation of results in various visual forms to investigate methodological bases for detecting practicing managers' views on future disruption in their industries. We proposed a method that combines and extends previously introduced methods, and thus we make the following main contributions. First, the proposed method can be used to efficiently and quickly capture practicing managers' perceptions of a systemic change in their business environment. Second, we employed seminar-based sampling in combination with the above to involve the wisdom of crowds of experts. Third, we employed experts from different parts of the value chain in order to detect possible discrepancies and similarities among their views.

By design, the seminar approach ensured that the audience represented the desired profile in terms of role and position in the value chain. After each session, some of the respondents were interviewed about the methodology; the formatted introductions and the VAS were appreciated. The sample size of the eight seminars yielded 278 respondents, which, with 18 sub-populations would limit generalization if used as a stand-alone methodology. Half of the seminars were company-specific or by invitation only, and half were open. The open seminars had a more random representation. The formatted process with the simple VAS was productive, and the method can easily be applied to grow the database for more statistical analysis, building comparative data for user segments other than machine-building, or repeating the study to detect a change in judgments over time.

From the technical point of view, the formatted process worked well, and the response rate from the audience was 100%. Of the responses, only four were rejected due to missing background information; fewer than 0.5% had unanswered items, and even these involved a maximum of two missing data points. Completion reduced the natural variance somewhat, but due to the very low number of missing data points, this had a marginal impact on the conclusions. Use of univariate plots and diagrams of strong opinions enabled fast conclusions about the practitioners' perceptions, including consensus or disagreement in the value chain. The results were translated from the VAS to numerical values. The additional benefit of the VAS is that the data allow more granular analysis to be done at a later stage if new data are collected.

Non-response issues and low response rates present serious threats in empirical research, and these concerns have recently seen a sharp increase, owing to increasing use of web surveys (Sauermann and Roach, 2013). The proposed method builds on organized seminars and the use of participants in order to increase response rates. This naturally eliminates non-response bias possibilities while introducing other possible sources of bias, such as selection of invited participants. However, the source of these biases can be controlled for with careful study setting. We tested the VAS-based method with a heterogeneous audience in the machine-building industry. The results are promising, in that group differences are detected, and, theoretically, we found justified differences. Therefore, the proposed VAS-based method may provide an interesting testing ground for increasing response rates and improving survey-based research, as it can be scaled to web-based queries.

4.1. Implications for practice

Apart from these methodological contributions, we may draw a number of practical implications from our results. However, as the majority of the users were container terminals, the applicability of the conclusions is limited. The business environment and the market structure are, however, similar in many traditional machine-building industries, such as machine-building serving mining. Therefore, there are likely some learning points applicable beyond the container handling context. The three main conclusions are as follows.

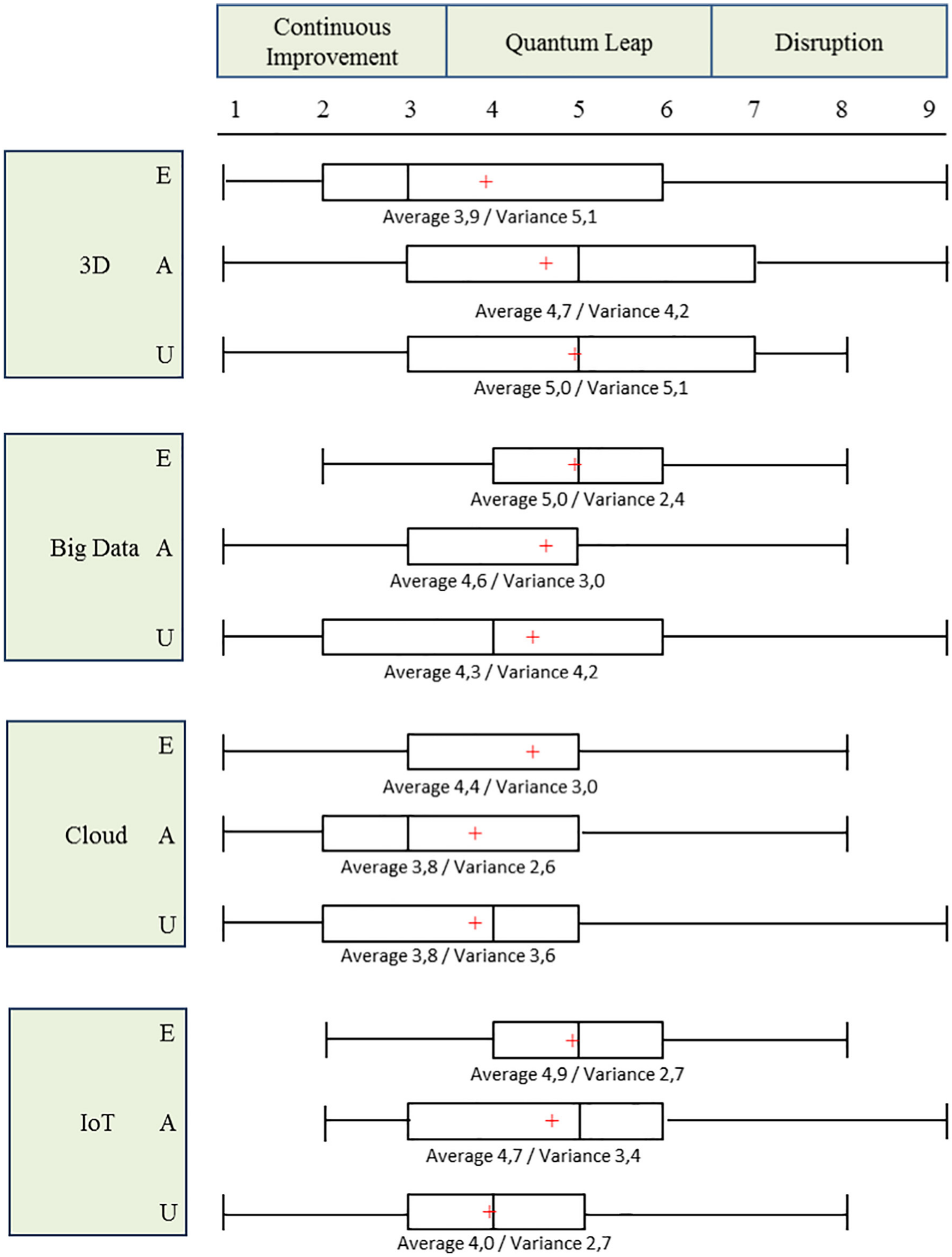


Fig. 5. Disruptiveness of individual technologies or concepts by value chain, balanced data.

1) For the incumbent machine-builder, the most attractive route to transform the industry is through services

Spare parts represent a razorblade business model for a machine-builder, which implies that service business is a high-margin business to defend. Using big data/AI with IoT and cloud presents an attractive growth opportunity. This notion is also important in the II. Logically, disruption by out-of-industry players is limited if solutions require deep knowledge of the machinery.

A larger step in the business models is what is described by World Economic Forum (2015) as the outcome economy, by Porter and Heppelman's (2014) as the systems of systems, and by Zysman et al. (2013) as services with everything. The disruptive element in the transformation is platforms (Gawer and Cusamo, 2002), if they allow out-of-industry complementors in value creation. The platform can decouple the value chain and allow OI (Chesbrough, 2006) principles to be applied. In the definition of the actor, it was noted that machine-builders integrate external technology as part of their solutions for

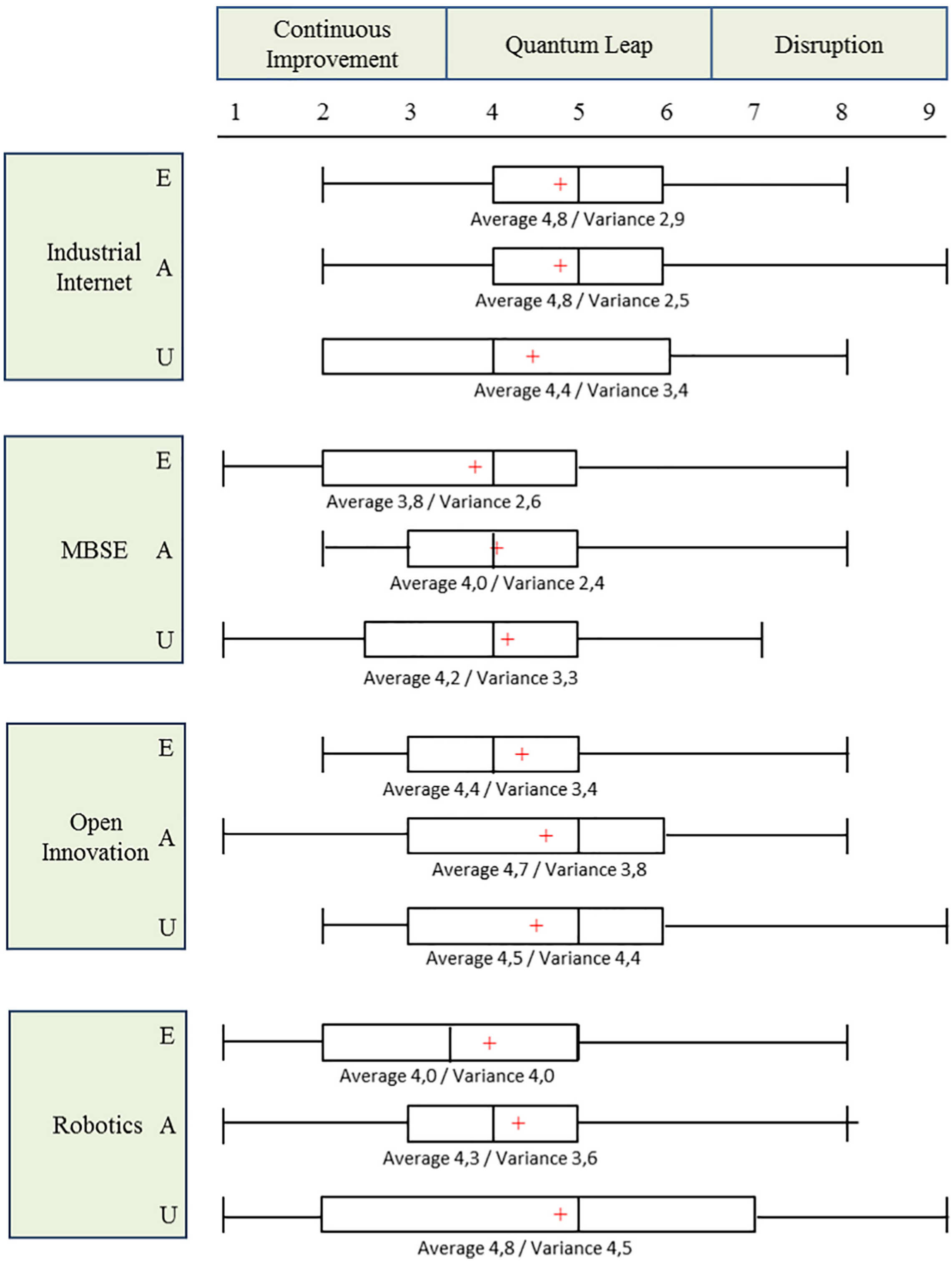


Fig. 6. Disruptiveness of individual technologies or concepts by value chain, balanced data.

users. Platforms also enable some of these technology suppliers to bypass the actor, depending on how critical the technology is in the user's process. In a knowledge-based disruption, the user plays a key role when defining the rules for opening up its data externally. The example of precision farming in Porter and Heppelman's (2014) article shows that this development is already here.

The theoretical contribution of this paper relates to the contraction of the seminal theory of Five Forces (Porter, 1979), used by practitioners, where platforms and attached networks are missing from the model. One can argue that the theory might be useful at the stage when systems compete with each other or with platform suppliers. However, the missing elements reduce the applicability of Five Forces as an explaination of the dynamics from the product business to the outcome economy or competition between systems and networks.

The second practical contribution is related to strategy formation. The data do not validate the preferred actions but instead validate the systemic and unpredictable nature of the business environment.

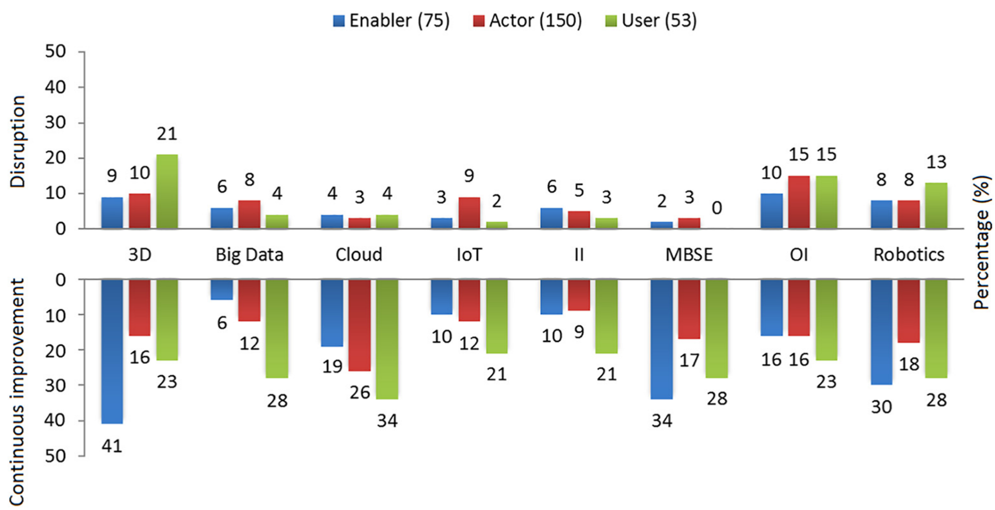


Fig. 7. Weak and strong disruption drivers by value chain, balanced data.

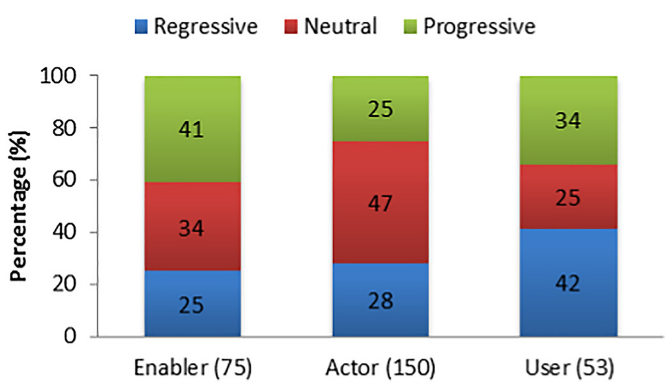


Fig. 8. Impact of own digitalization investments, balanced data.

2) Learning and experimentation is a core element in strategy formation in digital transformation

A prerequisite for choice of strategy is agreement on the nature of the change in the business environment and the importance of the potential impact of digitalization. This is not self-evident, as suggested by the various management cognition theories. If agreed, then the learning strategy suggested by Minzberg et al. (1998) and the experimentation suggested by Ries (2011) become good options. The transformation journey is also a governance question, and in addition to a generic structure or governance choices, Porter et al. (2015) offered three types of approaches to digital transformation: stand-alone business units, centers of excellence, and cross-business-unit steering.

Forming a strategy by learning and experimenting not only makes for a better strategy but also builds the capabilities that are needed in digital transformation. The systemic nature of the transformation also suggests that the needed capabilities require simultaneous mastering of many disciplines.

3) Strong machine-building and industry knowledge constitute a unique core competitive capability when combined with various digital technologies

The assumption in this notion is that the incumbent machine-builder (the actor) possesses strong engineering and industry capabilities that have enabled its current position. These capabilities are not likely to become irrelevant as long as the real process adds value to physical processes in which large quantities of material are processed, lifted, handled, and transported. It is obvious that if AI, robotics, or 3D printing enables disruptive development for the firm, one should also build the capabilities needed for those technologies. Perhaps the capabilities related to the de-coupling of value chains into networks pose a greater challenge. De-coupling requires network orchestration capabilities from practicing managers, but it also changes the way in which value is created. It is certainly more than a make-or-buy decision.

4.2. Discussion

Our method can capture the perceptions of respondents efficiently and quickly. We propose a method that gathers experts' opinions of a possible future systemic change using a relatively simple VAS–based survey instrument. We targeted our VAS-questionnaire toward ex-ante identification of the disruptive nature of changes taking place in the business environment. Traditional methods -including Delphi or similar survey-based methods, action research, and interview questionnaires- require a lot of effort, time, and resources in addition to the need to include many questions representing complex issues. The use of VAS in evaluating systemic, possibly disruptive, change is novel and relies on heuristic decision-making involving complex issues. In particular, this type of employment of heuristics of experts may provide insights into complex issues when changes have low predictability and perceptions are drawn from data samples that are small considering the extent of the change (Gigerenzer and Gaissmaier, 2011).

We also propose a seminar-based sampling method in order to attune respondents to the topic and gather experts from the field of enquiry. This leads to efficient use of respondents' time, as they respond in the course of a seminar that they would have been attending anyway; it also reduces the risk of research setting-induced bias, researcher-induced persuasion, and similar sources of bias (Chaiken and Maheswaran, 1994). The seminars dealt with various aspects of systemic change, digitalization, and new business trends, and respondents were attuned to the topics beforehand, as they enrolled in the seminars and were therefore already contemplating the changes in their business environment. Recent reports indicate that dominant logic based on experience may positively influence decision-making and views on complex phenomena in business environments (Matysiak et al., 2018).

As part of the seminar-based method, we were also able to guarantee the suitability of the respondents (i.e., their background throughout the value chain). The importance of understanding the perceptions and views of various stakeholders in innovation ecosystems and networks has recently been emphasized (Klenner et al., 2013). The participation of informants from different parts of the value chain also presented us with the opportunity to compare views across the value chain and gather differently biased perceptions. This was done expressly to gain expert perceptions with opinions and biases, as biased views have been shown to possibly lead to better decision-making and more accurate views on complex changes (Gigerenzer and Brighton, 2009).

The first practical implication of our results points clearly to the perception of the rising importance of services instead of purely goods-based business, in line with the existing literature (Vargo and Lusch, 2004). However, in order for incumbents to move toward more service-centric operational modes, they need to learn from new technology providers and actors in the marketplace, and this may prove to be problematic (for example, because of differences between new and old organizations) (Lane and Lubatkin, 1998).

In order for the required learning to take place, experimentation is imperative, as the business environment changes. The purpose of experimentation is to purposefully seek a suitable process of trial and error with a feedback loop to strategic planning (Nicholls-Nixon et al., 2000). Entrepreneurial companies naturally operate in this fashion, but incumbent companies need to seek this type of operational mode vigorously and with determination in order to overcome their inertia (Romanelli and Tushman, 1986).

Finally, our practical implications underline the opportunities incumbents have in combining their existing competences with new capabilities provided by technological evolution. This requires internal knowledge, capability development, and collaboration with external parties. To avoid pitfalls along this road, incumbents need to determine strategically which competences should be developed and with whom (Hamel, 1991).

4.3. Limitations and future research avenues

This paper investigated a method for quickly capturing practicing managers' perceptions of systemic change in their business environment. To mitigate technical problems, the paper-and-pen method was used to complete the survey instead of an electronic interface. Thus, an obvious future research avenue would be improving the method to make use of crowdsourcing with a larger number of participants; this may be, according to current knowledge, a promising avenue, even with non-experts (Lang et al., 2016). The method could use an inbuilt smart phone application attached to an online database with inbuilt analysis algorithms. A simple user interface and immediate feedback for the audience would also lower the barriers to the collection of new data.

The proposed method was shown to work in practice. Seminar organizers accepted the method, as the process took only 15 min, and the attendees were motivated to fill out the survey. The attendee lists also showed that it was possible to receive input from senior management, which is normally hard to get. However, although the response rate was close to 100%, the method was characterized by the sampling issues characteristic of surveys. This implies that seminar selection is critical when applying the method. Exchanging the paper-and-pen method for an electronic interface is essential for significant scaling of the method, and this would also speed up the process of analysis. Quick analysis is a prerequisite for integrating the method into companies' procedures for continuous scanning of the business environment.

The business environments of global machine-builders share many characteristics. Typically, the number of buyers and sellers is limited, entry barriers are high (as products contain a lot of accumulated knowledge), and the equipment is a critical asset in the user's process (implying high uptime requirements). Similarities in the business environment are likely to imply homogeneous needs in digitalization. However, the maturity of different user industries in terms of digitalization is likely to vary; for example, automation is a sensitive issue for unions, and unions have different positions in different industries. Similarly, the innovation phase in relation to unique industry characteristics may influence judgments, perceptions, and future transition paths. Together, these factors limit how far our results are generalizable beyond the context of machine-builders working in ports and terminals.

Further, some of the results might have cultural limitations as the respondents were mostly from Nordic and Central European countries. This could result bias; for example, judgment of OI is related to strong peer-to-peer relations instead of hierarchies and, consequently, has different values attached to it depending on respondents' cultural backgrounds.

The most logical area for further study would run the same research with enablers and actors from the same background but would focus on seminars that bring in respondents from user industries other than ports and terminals. This would increase understanding of the readiness of different users for digital transformation. With larger populations, one could also apply advanced statistical analysis.

The development of many digital technologies is rapid, as is the popularization of disruptive use cases. This implies that the current situation at ports and terminals might differ from that in 2015 when the majority of the data were collected. Repeating the study would reveal this temporality. Gartner, which for 20 years has published its hype curve of emerging technologies (LeHong et al., 2014), provides one benchmark against which the results of replication studies could be compared.

Our method rests on the logic of gathering a large number of perceptions of the nature of systemic change from boundedly rational (Tversky and Kahneman, 1973) agents. From existing empirical evidence, we found that some groups have more homogeneous perceptions than others. This opens up interesting questions for future research. For example, is bounded rationality tied to the context and content of the respondent's role in the value chain? Do shared cognitive biases that are built into an industry's practices and processes guide perceptions of future change? These types of questions could be tested in future research by building on the VAS approach we devised. Theoretically, these lines of investigation would extend and improve the bases for anticipating disruptive changes and building forward-looking (Rohrbeck et al., 2015) search processes in organizations. Furthermore, our finding that views of the nature of disruptive change depend on the position of the respondent in the value chain appears paradoxical, in that it is both expected and surprising. It is expected in the sense that we can assume that respondents from different industries view systemic changes differently; it is surprising in the sense that traditionally disruptive change has not been considered context-specific. This nature of context specificity calls for theoretical and empirical future investigations in the theory of disruptive innovation.

Mixed methods is research presents another possible future avenue. In this case, it is logical that in-depth interviews with informants with the same roles and position in the value chain would provide additional depth for the analysis of the results. Such interviews would also provide insight into the reasons why informants judge the future impact or drivers in the way they do. Another suitable mixed methods approach would be to use big data, such as applying text mining to the professional discussions conducted by the same experts in seminars, trade media, and other professional platforms.

Appendix A. Questionnaire used in our study

Developer			
Decision-Maker			
	Enabler	Actor	User

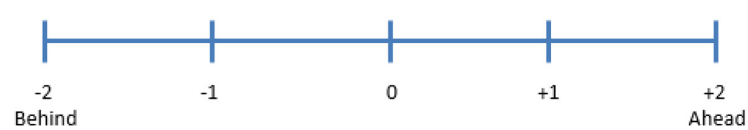
The impact of digitalization to machine building in your opinion

	Continuous improvement	Step change	Disruption -5,5-10,+10 y.		
Future products					
Timing if disruption					
Future services					
Timing if disruption					
Future operations					
Timing if disruption					
Future business models					
Timing if disruption					

The relative importance of drivers causing the impact

	Continuous improvement	Step change	Disruption
AM (3D printing)			
Big Data			
Cloud			
Internet of Things			
Industrial Internet			
Model Based System Engineering			
Open Innovation			
Robotics			

Where does your current investment (infrastructure, people, R&D, process and IT development ...) get you relative to your peers considering also your judgement of the digitalization impact?



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