“Big brother is watching you”: surveillance via technology undermines employees’ learning and voice behavior during digital transformation

Julia M. Kensbock¹ · Christoph Stöckmann²

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Abstract

In the digital age, the ability of organizations to create innovation is more important than ever before. By taking an employee perspective to digital transformation, we examine two important and inter-related cornerstones of organizational innovation—employees’ intrinsically motivated learning (i.e., their learning orientation) and employees’ willingness to speak up and raise constructive suggestions (i.e., their voice behavior). We conducted a survey study with 100 employees working in industries that are currently disrupted by digitization. Supporting the idea of self-determination theory, our findings show that digital transformation triggers employees to engage in an intrinsically motivated process during which they adopt a learning orientation, which consequently motivates them to express voice behavior. However, this beneficial process is counteracted by perceived surveillance via technology. When employees feel that digital transformation is accompanied by increased surveillance, they are less likely to adopt a learning orientation and therefore less likely to engage in voice behavior. Theoretical as well as practical implications are discussed.

Keywords Digitization · Digital transformation · Surveillance · Learning · Voice behavior

JEL Classification M12 · O15

✉ Julia M. Kensbock
j.kensbock@maastrichtuniversity.nl

¹ Department of Organisation, Strategy and Entrepreneurship, School of Business and Economics, Maastricht University, Tongersestraat 53, 6200 Maastricht, Netherlands

² Department of Business Administration, Seeburg Castle University, Seekirchen am Wallersee, Austria

1 Introduction

The ongoing emergence, rise, and advancement of pervasive digital technologies is radically affecting the world of business (OECD 2017; Bannier and Breuer 2017). Some of the most relevant—and most disruptive—digital technologies include social, mobile, analytics, cloud, and internet of things technologies, as well as combinations of these (Sebastian et al. 2017; Vial 2019). The ongoing digitization changes customer behavior and significantly disrupts the competitive landscape by bringing new players with digital business models into the market (Vial 2019). Digital technologies can provide “both game-changing opportunities for—and existential threats to—companies” (Sebastian et al. 2017, p. 197). On the opportunity side, numerous highly innovative business models successfully transform entire industries (Nambisan et al. 2017). On the threat side, many established firms fail to keep pace with digital innovations and get surpassed by young and innovative digital ventures (Verhoef et al. 2019). Consequently, the ability to develop digital innovations is becoming increasingly essential for firm survival and success in the digital world (De Sordi et al. 2016). Many established firms are just now beginning to engage in digital transformation, that is, to adapt their businesses to digitization (Berman 2012; Nambisan et al. 2019). Benner and Tushman (2015) thus declared innovation research to be at a transition point and called for future studies that consider how digitization affects innovation development within organizations.

Digital transformation is a pervasive change process that affects employees at all levels of the organization, fundamentally reshapes job demands and work routines, and forces employees to rethink prior approaches to their work (cf., Shoss 2017; Van Knippenberg et al. 2015; Yoo et al. 2012). Consequently, employee motivation and behavior in times of digital transformation—their willingness to adapt to, but also to actively support digital change—will be key to the effectiveness of digital transformation (cf., Oreg et al. 2011). Given the wide-ranging consequences of digitization for organizations, it is surprising that empirical insights into employees’ reactions to digital transformation are scarce.

Following the notion that “innovation starts with people” (van Laar et al. 2017: 577), we suggest that successful innovation and digital transformation—particularly in the digital age—depend on employees’ ability to identify room for improvement and their subsequent willingness and to raise constructive ideas and suggestions. We thus examine two central cornerstones of innovation on the employee side. The first cornerstone, which equips employees with the ability to develop innovative ideas, is their intrinsically motivated learning orientation (Button et al. 1996). Through learning, employees develop the capability to integrate complex and heterogeneous knowledge, which facilitates the creation of digital innovation (Yoo et al. 2012). Related to that, the OECD (2016: 44) recently proclaimed that “ICT-related skills are a key enabler of digital innovation”. Thus, we suggest learning to be a necessary step enabling employees to develop ideas.

However, merely developing innovative ideas is not enough. As a subsequent step, employees’ ideas can only turn into action when they are articulated

(Guzman and Espejo 2018). Thus, the second cornerstone and final outcome of the present study is voice behavior, which reflects employees' willingness to make new suggestions and articulate ideas (LePine and Van Dyne 1998). Voice behavior is thus considered an essential step in the innovation process (Fuller et al. 2006). Given that the motivation to develop and the willingness to raise innovative ideas naturally interlock, we conceptualize learning orientation and voice behavior as two inter-related parts of an overall, intrinsically motivated, process. Drawing on self-determination theory (Deci and Ryan 1985; Ryan and Deci 2000), we suggest that digital transformation encourages employees to engage in that intrinsically motivated process, that is, to adopt a learning orientation and consequently to engage in voice behavior.

While the rapid development and spread of digital technology increases firms' dependence on their employees' innovative ideas, this digitization simultaneously enables organizations to observe and monitor employees in ways that we could not have foreseen 50 years ago (Bernstein 2017; Solon 2017). Employee surveillance via technology is a phenomenon that is exponentially growing (Bernstein 2017; Levy 2015), intensively discussed in public media (e.g., Solon 2017, 2018), but still under-researched (Anteby and Chan 2018). Surveillance is defined as a "close, constant, and comprehensive supervision of a comprehensive set of activities, behaviors, and personal characteristics of the observed" (Bernstein 2017: 78). New technologies give organizations the opportunity to supervise their employees in "real time", e.g., using wearable wristbands for tracking warehouse workers (e.g., Solon 2018). However, also less extreme cases of surveillance are gradually entering ordinary workplaces (Bernstein 2017). This includes, among others, tracking employees' performance (e.g., output, phone call content, location), or observing their personal characteristics (e.g., e-recruitment, data mining) (Ball 2010). From a management perspective, employee surveillance via digital technologies offers various benefits. It helps firms to monitor and thereby to increase employee performance (Moore 2000), to ensure employees' compliance with rules (Subašić et al. 2011), and to provide employees with feedback (Niehoff and Moorman 1993). However, employees often react in negative ways when they are being monitored. Among others, surveillance is associated with high stress, low levels of job satisfaction, and high turnover (Chalychoff and Kochan 1989; Holman et al. 2002).

Given that surveillance can threaten employee motivation and performance (e.g., Allen et al. 2015), the question arises as to how being "watched" at work affects employees' intrinsic motivation to learn and, consequently, their willingness to speak up, both of which is essential for firms undergoing digital transformation. We thus follow the recent call by Bernstein (2017) to combine research on employee voice behavior with research on surveillance. Following cognitive evaluation theory (Deci and Ryan 1985), we introduce perceived technological surveillance as an important moderator to the intrinsically motivated process of learning orientation and subsequent voice behavior. We argue that when employees experience constant surveillance, their intrinsically motivated learning orientation will be undermined, finally leading to decreased voice behavior. Taken together, in the light of the increasingly radical technological advancements, we deem it important to explore how digital transformation and surveillance opportunities affect employees'

engagement in intrinsically motivated learning and voice behavior. Based on this research objective, our two-fold research question is: (a) How does digital transformation affect employees' learning orientation and voice behavior and (b) how does perceived surveillance undermine this intrinsically motivated process?

We empirically test our assumptions in a quantitative study with 100 employees within two industries (publishing industry and travel industry) that are intensively affected by digitization. Within that sample, we find support for our idea that digital transformation triggers a mediation effect of increased learning orientation and increased voice behavior in employees. However, we also find that perceived surveillance via technology undermines this process. That is, the more employees in our sample felt monitored via technology, the less they engaged in learning behavior and consequently voice behavior.

Our study contributes to three distinct streams of research. First, we provide a novel and much-needed psychological perspective to the digitization literature. We thereby add to an emerging stream of research that has mostly focused on the technology or business model side of digitization (e.g., Nambisan 2017; Tilson et al. 2010), but mostly neglected to consider the “human factor”, that is, how employees react to digital transformation. Second, in focusing on the role of employees during digital transformation, we also advance knowledge within the innovation management domain. In examining how and under which conditions digital transformation triggers employees to engage in intrinsically motivated learning and voice behavior, our study contributes to understanding the roots of digital innovation. Third and finally, we contribute to the managerial control and surveillance literature. While prior research has often portrayed surveillance as a useful management tool (e.g., Niehoff and Moorman 1993), we provide particularly shed light on the “dark side” of surveillance, especially in the digital age.

The paper proceeds as follows. In the next section, we introduce self-determination theory as a framework for understanding employee reactions to digital transformation. We hypothesize that digital transformation triggers an intrinsically motivated process of learning orientation (mediator) and voice behaviour (outcome). Moreover, based on cognitive evaluation theory, we suggest that perceived surveillance via technology moderates the link between digital transformation and learning orientation, thereby also indirectly affecting voice behaviour (moderated mediation). After discussing our results and implications for theory and practice, we close by outlining the limitations and identifying promising lines of future research.

2 Theory and hypotheses

2.1 Self-determination theory as a framework for understanding employee reactions to digital transformation

The present study examines the reactions of employees who are confronted with changes to their work environment due to digital transformation. We suggest that these employee reactions can be best explained by considering the perspective of self-determination theory and the associated sub-theory of cognitive evaluation

(Deci and Ryan 1985; Ryan and Deci 2000). According to self-determination theory, individuals have an inherent need to strive for autonomy and competence (Ryan and Deci 2000). Self-determination theorists think of human beings as proactive, curious, and self-motivated. They assume that individuals, by their very nature, strive to learn, extend themselves, master new skills, and take responsibility (Ryan and Deci 2000). Building on these insights, we suggest that digital transformation has the potential to elicit an intrinsically motivated process that consists of learning orientation as a direct outcome (reflecting employees' intrinsic motivation to learn and develop) and voice behavior as an indirect outcome (reflecting employees' intrinsically motivated behavior). Thus, as a response to digital transformation, we expect employees to adopt a learning orientation, which consequently motivates them to engage in voice behavior.

At the same time, cognitive evaluation theory—a sub-theory of self-determination theory (Deci and Ryan 1985)—admits that the above-noted intrinsic motivation of humans to learn and develop does not always turn into reality. Instead, the theory suggests that intrinsic motivation can be undermined when individuals feel that they are being externally controlled (Deci and Ryan 1985). One key factor that can create the feeling of being externally controlled is surveillance (Lepper and Greene 1975). We thus suggest that perceived surveillance via technology will undermine the intrinsically motivated process described above. We expect that when employees feel that digital transformation is accompanied by surveillance, they will be less likely to adopt a learning orientation and will thus be less likely to express voice.

In the following sections, we will first outline a mediation process of digital transformation on voice behavior via learning orientation. Building on self-determination theory, this mediation represents the intrinsically motivated process that we suggest being the “default reaction” of employees during digital transformation. We will then introduce the moderating, undermining effect of perceived surveillance on that intrinsically motivated process, leading to a moderated mediation hypothesis. The overall research model is displayed in Fig. 1.

2.2 Impact of digital transformation on employees' learning orientation

Digitization is an overarching disruptive sociotechnical phenomenon affecting entire industries (Nambisan et al. 2017). It urges established organizations to adapt their

Fig. 1 Research model. The solid arrows indicate the main effects of digital transformation on learning orientation (H1) and of learning orientation on voice behavior (H2). The dashed arrow indicates the mediating effect of digital transformation on voice behavior via learning orientation (H3). The bold gray arrow indicates the interaction between digital transformation and perceived surveillance on learning orientation and subsequently voice behavior (moderated mediation; H4)

business models and processes, that is, to engage in a digital transformation process. Using the terminology of organizational change management, digital transformation can be described as a transformational change. Transformational (as compared to incremental) change processes have a major impact on organizations (Levy 2015) and constitute a “shock to the system” (Rafferty and Jimmieson 2017: 250). In the present study, we focus on digital transformation, as perceived by the employees within organizations. This is relevant, because digitization, in many cases, triggers pervasive change processes within organizations that immediately affect employees’ job demands and working environment (Shoss 2017; Van Knippenberg et al. 2015). Digital transformation thus confronts employees with a new organizational reality (Tilson et al. 2010) and fundamentally changes how individuals work together (Dougherty and Dunne 2012). Consequently, during digital transformation, employees can no longer rely on knowledge, skills, routines, and processes that they have previously used. Instead, the disruptive changes create an urgent need for employees to learn and develop. Digital transformation makes employees’ job tasks increasingly complex and interactive (van Laar et al. 2017). Consequently, employees do not only need to develop excellent skills for using novel technologies at work, but also higher-level competencies for adapting to the changing overall job requirements (Carnevale and Smith 2013; van Laar et al. 2017).

Self-determination theory states that, in their “default setting”, humans are motivated to learn and develop new skills and competencies (Ryan and Deci 2000). Following that notion, we suggest that employees will perceive digital transformation as a learning opportunity. Specifically, when confronted with digital transformation, we expect employees to react by adopting a learning orientation, which reflects their intrinsic motivation to learn and develop in the work context (Janke et al. 2015). When individuals adopt such a learning orientation, they actively approach challenging tasks (Godshalk and Sosik 2003), develop new skills and capabilities, and increase their competence and mastery (Button et al. 1996). The adoption of a learning orientation can be influenced by situational factors, e.g., the organizational context (Button et al. 1996). We suggest that digital transformation is such an important situational factor that has the potential to elicit a learning orientation within individuals. This is because digital transformation serves as a “discontinuous learning event” (Cope 2003: 429)—a rapid change in the work environment (Dong et al. 2014) that puts employees into new situations in which they can no longer make use of the established routines and tactics that they have previously used (Preenen et al. 2011). Instead, these events create a state of disequilibrium forcing individuals to critically question whether their established skills and approaches are still adequate (McCauley et al. 2010). Supporting the notion of self-determination theory, empirical evidence shows that discontinuous learning events intrinsically motivate employees to acquire new skills (Dong et al. 2014).

Taken together, we suggest that the disruptiveness of digital transformation will make employees aware of the fact that many of their established approaches to working are no longer helpful and that they need to develop new skills and competencies. Following individuals’ inherent desire to grow and develop, digital transformation will encourage employees to adopt an intrinsically motivated learning orientation,

which is an expression of their desire to learn and develop new skills and competencies (De Bilde et al. 2011). We thus hypothesize that:

Hypothesis 1: Digital transformation will relate positively to employees' learning orientation.

2.3 Impact of employees' learning orientation on their voice behavior

Following self-determination theory, intrinsic motivation (as reflected in an intrinsic learning orientation) can in turn yield intrinsically motivated behavior among employees (Gagné and Deci 2005). Thus, as the second part of the intrinsically motivated process, we suggest that adopting a learning orientation will make employees engage in increased voice behavior. Employee voice behavior is defined as "speaking out and challenging the status quo with the intent of improving the situation" (LePine and Van Dyne 1998: 853). Voice behavior has a beneficial impact on organizations, as it leads to higher-quality organizational decision-making (Burris 2012), heightened organizational effectiveness (Maynes and Podsakoff 2014), and increased competitiveness (Liu et al. 2010). Most importantly, employee voice behavior closely relates to innovation. By challenging the status quo in an organization, voice behavior prompts active new methods of thinking and new pathways for success (Liang et al. 2012). This enables organizations to develop innovative solutions in fast-changing competitive markets (Detert and Burris 2007).

A learning orientation is associated with approach-oriented behavior (Elliot 1999). When adopting a learning orientation, individuals actively seek challenging and stimulating tasks that provide them with the opportunity to learn and to gain new skills (Preenen et al. 2014). A learning orientation enables deep processing (Zhu and Akhtar 2017), that is, to integrate the novel information with prior knowledge and experience (Elliot et al. 1999). That way, employees with a learning orientation should be more likely to detect and realize inconsistencies or problems within the tasks that call for improvement. Consequently, they are more likely to express voice behavior in order to reduce discrepancies between a current (unsatisfactory) state and a future (desired) state (Kakkar et al. 2016). In addition, a learning orientation may equip employees with the courage needed to express voice behavior. Since voice behavior often challenges how things are done in an organization, it can be perceived as socially risky (Morrison and Rothman 2008). Among others, employees might be reluctant to speak up, because they fear being viewed as a complainer, upsetting others, or losing others' support (Morrison 2014). However, since individuals with a learning orientation are willing to take risks to achieve their goals (Scholer et al. 2010), they may also be more willing to take the social risk of speaking up. Finally, employees with a learning orientation strive not only to develop, but also to show their competence (Kakkar et al. 2016). Since publicly expressing ideas or suggestions is seen as an indicator of competence (Whiting et al. 2008), voice behavior will fulfil the needs associated with a high learning orientation. In sum, we suggest that employees who adopt a learning orientation will be more likely to engage in voice behavior.

Hypothesis 2: Employee learning orientation will relate positively to employee voice behavior.

2.4 Impact of digital transformation on employee voice behavior via learning orientation

Taken together, we suggest that digital transformation will trigger employees to engage into an intrinsically motivated process consisting of two inter-related key components: employee learning orientation (reflecting their intrinsic motivation to learn and develop) and voice behavior (reflecting their intrinsically motivated behavior to change things around them). Scholars often distinguish between individuals' ability and willingness required to perform various kinds of behavior (e.g., Martin et al. 1990; De Massis et al. 2014; Minbaeva and Michailova 2004). Based on that notion, we understand employee learning as the key motivational process that equips individuals with the necessary ability to engage in innovative behavior. That way, learning orientation is the central driving force in our research model and sets the ground for employees' subsequent willingness to actively support digital change in the form of voice behavior. As a discontinuous learning event, digital transformation will evoke a learning orientation within employees and thereby enable them to integrate the complex and heterogeneous knowledge needed to develop new ideas (cf., Yoo et al. 2012). Further, we suggest that once employees have developed new knowledge and ideas, they will be more willing to express voice behavior to actively support digital change (cf., LePine and Van Dyne 1998). Taken together, we hypothesize employee learning to be the essential linking pin that translates how digital transformation can increase employee voice. We thus expect employees' learning orientation to act as a mediator that translates the impact of digital transformation on voice behavior:

Hypothesis 3: Learning orientation mediates the relationship between digital transformation and employee voice behavior, such that digital transformation positively affects learning orientation, which then positively affects employee voice behavior.

2.5 Digital transformation, learning orientation, and voice behavior: the moderating role of perceived surveillance

The ongoing digitization not only increases firms' dependence on their employees' innovative ideas, but also enhances firms' technological possibilities to monitor their employees. We suggest that perceived surveillance has the power to undermine the positive effect that digital transformation is expected to have on employees' intrinsic learning orientation and on their subsequent voice behavior. The idea that surveillance undermines intrinsic motivation can be explained by cognitive evaluation theory, a sub-theory of self-determination theory (Deci and Ryan 1985). Cognitive evaluation theory suggests that the intrinsic motivation that individuals would naturally pursue according to self-determination theory does not always come into

action, because critical extrinsic factors can undermine it (Deci and Ryan 1985). The most prominent studies in the domain of cognitive evaluation theory show that when individuals are offered monetary rewards for doing a task for which they are intrinsically motivated, they feel controlled by the reward and consequently lose their own intrinsic motivation and interest in the task (Deci 1971, 1972; Ryan 1982). However, this undermining effect of intrinsic motivation does not only pertain to monetary rewards, but to any extrinsic factor that diminishes individuals' feelings of autonomy.

We suggest perceived surveillance to be such an external factor that thwarts employees' feelings of autonomy, thereby preventing them from adopting a learning orientation. This is because employees often perceive surveillance as a privacy invasion (O'Donnell et al. 2010). Given that surveillance characterizes "the few watching the many" (Sewell and Barker 2006: 935), it is a tool of hierarchical leadership power and sometimes perceived as a tool of oppression (Bernstein 2017; Levy 2015). When employees are under constant surveillance, their supervisors' power and social control is omnipresent (O'Donnell et al. 2010; Sewell and Barker 2006). From an employee perspective, surveillance "suggests an authoritarian approach to management, in which an Orwellian 'Big Brother' tries to watch and control the behavior of each employee" (Niehoff and Moorman 1993: 528). At the same time, individuals perceive surveillance as a violation of trust from their supervisors and reduce their work effort (Pierce et al. 2015; Subašić et al. 2011). Under these conditions, it is likely that employees lose their feeling of acting autonomously. Instead, under high perceived surveillance, individuals feel controlled by the surveillance, such that they perceive themselves only to perform because they are constantly watched (Lepper and Greene 1975).

Evidence for the undermining effect of surveillance on individuals' intrinsic motivation comes from a variety of studies. In a classic experiment, Lepper and Greene (1975) informed some of their participants that their performance would be monitored by a supervisor via a television camera. These participants (in contrast to those who were not monitored) appeared to be less intrinsically motivated and performed worse. The undermining effect of surveillance also showed in organizational settings. Watson and colleagues (2013) demonstrated that surveillance decreased employees' learning efforts in an e-learning setting. In addition, several studies approached the phenomenon from an opposite perspective, that is, by examining the impact of privacy (i.e., reduced surveillance) on employee outcomes. That way, Bernstein (2012) found that privacy encouraged employees to engage in experimentation and innovative problem-solving, consequently leading to higher job performance. Alge et al. (2006) showed that privacy positively affected perceived control, empowerment, and organizational citizenship behavior among employees.

Following that argumentation, we suggest that under high surveillance, digital transformation will no longer lead to an intrinsically motivated learning orientation, which will consequently decrease employees' likelihood to express voice behavior. That is, when employees perceive digital transformation to be accompanied by increased surveillance, they will be less intrinsically motivated to proactively acquire novel skills and competencies for the digital age. Following that low intrinsic learning orientation, employees will also be less motivated to offer suggestions that could

make a positive change for the organization (voice behavior) and will remain silent instead. In an extreme case, employees might even feel that the main motivation of their organization to engage in digital transformation is that the novel, innovative technologies enable a closer surveillance of the workforce. Taken together, we expect that high surveillance will thwart the positive impact of digital transformation on learning orientation and consequently on voice behavior. Thus, we hypothesize:

Hypothesis 4: Perceived surveillance moderates the indirect relationship between digital transformation, employee learning orientation, and voice behavior. Digital transformation will be more positively related to employee learning orientation (and consequently voice behavior) when perceived surveillance is low rather than high.

3 Methods

3.1 Sample and data collection

Given that the goal of this study was to examine employee reactions to digital transformation in organizations, we needed to identify an appropriate sample that enabled us to observe these phenomena. Since our study focused on employee reactions, we decided to survey employees who are—in some way—affected by digital transformation processes happening in the firms they are employed in. Since our study also focused on digital transformation, we needed to preselect an industry context in which we would be able to observe the effects of digital transformation. The industry context needed to fulfil two main criteria. First, we needed to ensure that digitization would at all play a role within the industries observed. Thus, we decided to choose two industries where firms have been and are continuously facing the need to digitally transform themselves in order to keep up with quickly changing consumer expectations and with new innovative incumbents to the market. Second, in order to observe differences in employee reactions toward digital transformation, we simultaneously needed to ensure that there would be a certain variance in digital transformation across the different firms in the same industry. Thus, despite the high overall industry-level digitization, we assumed that firms within these industries would be likely to still differ in the scope and extent to which they would have reacted and adapted their processes in response to digitization.

The first industry was the (newspaper/book) publishing industry. Fulfilling our first criterion, the media industry is one of the industries that is most heavily disrupted by digitization (Grossman 2016; Karimi and Walter 2016). The daily paid circulation of newspapers has declined by 24 percent from 2005 to 2015 and, over the same period, revenues have declined by 60 percent (Newman et al. 2015). Customer preferences are changing along with the emergence and rise of digital technologies, including a large shift from paper to digital format for both newspapers and books (Mangani and Tarrini 2017). Fulfilling our second criterion, at the same time, publishing firms react differently to these digital changes in the overall industry. For instance, some publishing firms adapt the format of their content to new technologies (e.g., e-readers and multipurpose tablets), while others adapt their pricing

strategy or even their entire business models (Newman et al. 2018). Mangani and Tarrini (2017) summarize that, in terms of digital transformation, "the digital publishing industry is still heterogeneous" (page 19).

The second industry was the travel (agency/tour operator) industry. Fulfilling our first criterion, this has been identified as one of the industries that "is completely turned on its head in recent years, due to extreme digital transformation" (Newman 2018). The changes especially affect firms that offer professional services to end-customers, such as travel agencies or tour operators. Driven by technological change, travelers increasingly use digital platforms to book a vacation instead of seeking the support of local companies (Colangelo and Zeno-Zencovich 2016). Fulfilling our second criterion, at the same time, there is variance in how travel firms react to that increasing digitization. While some firms are at the forefront of adopting digital technologies (e.g., mobile integration, virtual reality, artificial intelligence), others still largely rely on personalized support of travelers (Bowen and Morosan 2018; Bughin et al. 2018).

Following prior approaches (cf., Kollmann and Stöckmann 2014), we drew upon the well-established Hoppenstedt database, which includes detailed profiles of all German companies with more than 10 employees or more than €1 million revenues. For the two preselected industries, the database includes a total pool of 6379 companies (publishing industry = 3190; travel industry = 3189). Since web surveys administered to an unknown group of participants often result in low response rates and low data quality (Roster et al. 2004, 2007), we decided not to send out unsolicited mass e-mail invitations to all these firms. Instead, we followed the finding that personalized pre-contacts with organizations facilitate the response rates for web surveys (Cook et al. 2000) and decided to pre-contact firms via phone in order to introduce our study and to encourage participation. For the sake of making the telephone contact feasible, we chose a random sampling approach to select a smaller sub-pool of 2294 firms (publishing industry = 1146; travel industry = 1148) from the overall pool. Such random selection (i.e., equal probability for all firms being chosen) made this sub-pool an unbiased representation of the overall firm pool and thus prevent a sample selection bias. After having established the personal contact via phone, we sent out 721 e-mails (publishing industry = 386; travel industry = 335) with personalized survey links to those employees that had expressed interest in our study. Overall, 393 participants (publishing industry = 205; travel industry = 188) accessed the survey and 181 (publishing industry = 90; travel industry = 91) completed it, resulting in a response rate of 25.1%. In the next step, we excluded all respondents who indicated that they held executive roles (CEO, higher-level managers) within the firms. This was because higher-level managers are typically the sources or creators of surveillance (Sewell and Barker 2006) and we were interested in the reactions of employees who may perceive surveillance by those higher up in the hierarchy. That way, selecting only individuals at the subordinate level enabled us—at least to a certain degree—to control for the position of the person who was responding to our survey. The data selection resulted in a final sample size of $N=100$ employees (publishing industry = 42; travel industry = 58).

Before analyzing the data, we examined whether it was justified to merge the respondents of the different firms and different industries together into one sample. Firms in both industries—publishing and travel industry—were comparable in firm

age, firm size, and revenue. Firm age, firm size, and revenue were also unrelated to our focal study variables (digital transformation, perceived surveillance, learning orientation, and voice behavior). Moreover, respondents from the two industries did not significantly differ in their responses to the focal study variables. Taken together, there was no reason to believe that our results would differ across firms and industries. This justified our approach to examine all respondents in one joint sample.¹

3.2 Measures

In order to ensure the reliability and comparability of our study, we used established measurement scales whenever possible. Table 1 shows all focal study variables and their respective items. Moreover, Table 1 shows the most important reliability statistics for the multi-item constructs used. As recommended, all item-total correlations exceeded 0.30 (cf., Nunnally and Bernstein 1994), which justifies their aggregation into the constructs. Moreover, all Cronbach's alpha values were above 0.70, as recommended (Nunnally 1978). As an additional reliability indicator, the composite reliability was higher than 0.60 for each construct (Bagozzi and Yi 1988). The average variance extracted (AVE) exceeded 0.50 for all constructs (cf., Hair et al. 2010), which further proves the internal consistency of the scales used.

Our approach of collecting both the independent and dependent variables from the same respondents at the same time might raise concerns that the relationships among study variables were due to common method variance (Podsakoff et al. 2003). We ran several additional tests for common method variance in order to minimize these concerns. A first indicator for common method variance would be that all study items are loading on a common factor. Thus, using confirmatory factor analyses (CFA), we compared our measurement model against a single-factor model. Our measurement model including all items and constructs showed a satisfactory fit ($\chi^2 = 77.11$; CFI=0.95; RMSEA=0.08; TLI=0.94). By contrast, the model in which all items were collapsed into one single factor performed considerably worse ($\chi^2 = 261.62$; CFI=0.68; RMSEA=0.20; TLI=0.60, $p < 0.001$), indicating evidence against common method bias. As a second test, we used the approach by Fornell and Larcker (1981) to examine the constructs' discriminant validity (and thus against common method variance). We thus compared the square root of AVE for each study construct with all bivariate correlations between study variables. The square root of AVE for any construct (0.80 for digital transformation, 0.83 for learning orientation, and 0.77 for voice behavior; see Table 1) was higher than any bivariate correlation between the constructs (values ranging from 0.16 to 0.48). These findings additionally indicate the discriminant validity of our study variables, i.e., that our items related more strongly to their own constructs than to other constructs in the survey.

Digital transformation Given that our study applies an employee perspective to digitization, we also examined perceived digital transformation from an employee

¹ Results for these tests are available upon request by the authors.

Table 1 Variables and items used in this study

Variables	Items	Cronbach's alpha	Average variance extracted	Composite reliability	Item-total correlations
Digital transformation (based on Rafferty and Griffin 2006)	<i>The following questions will be about the impact that digitization had on the company you are working in</i>	.83	.64	.84	
	To what extent have you experienced changes significantly changed your work unit's goals?				.72
	To what extent have you experienced changes that affect your work unit's structure?				.78
	To what extent have you experienced changes to the values of your unit?				.58
Perceived surveillance (based on Dewar and Werbel 1979)	<i>Some companies use computer monitoring, e-mail monitoring, phone monitoring, or security cameras. Your company may use technology to track your work in other ways as well. We are interested in how you personally feel about these things</i>	n/a	n/a	n/a	
	I feel that I am constantly being watched through the use of technology, computers, and software at work				n/a
Learning orientation (VandeWalle 1997)	<i>Please indicate how much you agree with the following statements about yourself</i>	.92	.69	.92	
	I am willing to select a challenging work assignment that I can learn a lot from				.83
	I often look for opportunities to develop new skills and knowledge				.79
	I enjoy challenging and difficult tasks at work where I'll learn new skills				.86
	For me, development of my work ability is important enough to take risks				.70
	I prefer to work in situations that require a high level of ability and talent				.81

Table 1 (continued)

Variables	Items	Cronbach's alpha	Average variance extracted	Composite reliability	Item-total correlations
Voice behavior (Vakola and Bouradas 2005)	<i>How often do you express your disagreements to your managers concerning the following issues?</i>	.74	.60	.81	
	... regarding company issues				.47
	... regarding my department's issues				.74
	... regarding my job				.53

perspective. To measure the perceived extent of digital transformation, as experienced by participants, we drew on Rafferty and Griffin's (2006) transformational change scale. We adapted the established scale such that the survey instructions explicitly stated that the items would be about the impact of the digitization on the company that employees were working in. A sample item is "To what extent have you experienced large scale changes significantly changing your company's goals?" Participant answered the three items on a 7-point Likert scale ranging from 1 ("not at all") to 7 ("a great deal"). Cronbach's alpha for the scale was 0.83.

Perceived surveillance Prior literature has offered different approaches to assessing surveillance or monitoring. In some studies, surveillance was experimentally induced (e.g., Subašić et al. 2011) or examined in interviews or case studies (e.g., Sewell et al. 2012; Watkins Allen et al. 2007). Out of the existing survey-based measures, many scales do not refer to the perception of surveillance per se, but to individuals' attitudes toward surveillance and monitoring, e.g., whether they perceive it as an invasion of their privacy (e.g., Alge 2001; Spitzmüller and Stanton 2006). Additionally, some studies capture surveillance in an objective way by using checklists in which participants indicate the presence or absence of certain monitoring techniques at work (e.g., Stanton 2000). Given that we were interested in the subjective perception of "being watched" by digital technology in the workplace, we chose to combine two approaches taken in prior literature. We adapted an item used by Dewar and Werbel (1979), which originally stated, "I feel that I am constantly being watched to see that I obey all rules pertaining to my job". This item captures the subjective nature of perceived surveillance very well—however, it is limited to the compliance with rules and not related to technology. We thus changed this item to "I feel that I am constantly being watched through the use of technology, computers, and software at work" (7-point Likert scale ranging from 1 "fully disagree" to 7 "fully agree"). Additionally, we followed the approach by Stanton and Weiss (2000) and introduced the above-noted item by stating, "Some companies use computer monitoring, e-mail monitoring, phone monitoring, or security cameras. Your company may use technology to track your work in other ways as well. We are interested in how you personally feel about these things."

Learning orientation We captured employees' learning orientation by using the 5-item learning orientation subscale of the work domain goal orientation scale introduced by VandeWalle (1997). A sample item is "I often look for opportunities to develop new skills and knowledge". Participants responded on a 7-point Likert scale ranging from 1 ("fully disagree") to 7 ("fully agree"). Cronbach's alpha was 0.92.

Voice behavior Employees' voice behavior was measured using the scale by Vakola and Bouradas (2005). Following their approach, we asked participants to indicate how often they express their opinion to their managers concerning (a) company issues, (b) department/team issues, and (c) their own jobs. Participants indicated the frequency of their voice behavior on a 5-point Likert scale ranging from 1 ("never") to 5 ("always"). Cronbach's alpha was 0.74.

Control variables Several individual factors might affect whether employees see digital transformation as a learning opportunity, thereby eliciting an intrinsically motivated process (as hypothesized in line with self-determination theory) or whether surveillance undermines this process (as hypothesized in line with cognitive evaluation theory). We therefore apply a number of control variables to our analyses. Since digital transformation and surveillance might affect male vs. female employees' intrinsic motivation and the expressed voice behavior differently (e.g., Johnson and Schulman 1989), we controlled for participants' gender. Likewise, we controlled for employees' age, because younger vs. older employees might differ in their likelihood to engage in learning and voice behavior (cf., LePine and Van Dyne 1998). We also followed LePine and Van Dyne's (1998) recommendation to control for participants' education (university degree or not), which could especially affect whether employees perceive digital transformation as a learning opportunity. In addition, we controlled for fear of failure as an important individual difference variable. Individuals high in fear of failure tend to avoid and withdraw from achievement situations (Elliot and Church 1997). That way, individuals low vs. high in fear of failure might also react differently to digital transformation, making them more or less likely to see this change as intrinsically motivating. We measured fear of failure with the five-item Achievement Motives Scale (Lang and Fries 2006). Cronbach's alpha was 0.84. Finally, since we combined participants working in two different industries, we controlled for industry (0 = travel agency/tour operator; 1 = newspaper/book publishing).

Table 2 Descriptive statistics and correlations among study variables

	Mean	SD	1	2	3	4	5	6	7	8
1. Digital transformation	3.79	1.48								
2. Perceived surveillance	2.39	1.48	-.02							
3. Learning orientation	5.02	1.28	.21*	-.21*						
4. Voice behavior	3.05	0.84	.22*	-.16	.48***					
5. Gender ^a	0.41	0.49	.02	.13	.05	-.08				
6. Age	34.89	10.94	.04	.11	-.05	-.01	-.06			
7. Education ^b	0.38	0.49	.07	-.07	.35***	.20	.07	-.02		
8. Fear of failure	3.16	1.25	.26*	.10	.02	.00	-.16	-.24*	-.10	
9. Industry ^c	0.42	0.50	-.14	.05	-.14	.12	.00	.16	-.03	-.12

N = 100

* $p < .05$

** $p < .01$

*** $p < .001$

^aFor Gender, 0 = "Female", 1 = "Male"

^bFor Education, 0 = "No University Degree", 1 = "University Degree"

^cFor Industry, 0 = "Travel/Tour Operator Industry", 1 = "Newspaper/Book Publishing Industry"

4 Analyses and results

Table 2 shows the descriptive statistics and the correlations among our study variables. Several issues deserve a closer observation. First, the correlations among our focal study variables indicated that digital transformation was positively linked with both learning orientation ($r=0.21$, $p<0.05$) and voice behavior ($r=0.22$, $p<0.05$). Second, learning orientation correlated positively with voice behavior ($r=0.48$, $p<0.001$). Third, the correlations of the control variables with the focal study variables were insignificant, except for participants' education. Education and learning orientation were positively correlated ($r=0.35$, $p<0.001$), indicating that participants with a university degree reported a higher learning orientation than participants without such a degree.

We tested our research model using the PROCESS macro for SPSS developed by Hayes (2013)—a widely-used tool that is based on ordinary least squares (OLS) regression. Given our hypotheses, we needed a reliable tool to test for indirect effects (mediation effects and moderated mediation effects). The PROCESS macro was chosen, because it relies on bootstrapping to determine confidence intervals for indirect effects (Hayes 2009). As a random resampling method, bootstrapping treats the study sample as if it were a population and draws a large number (5,000 in our case, as recommended by Hayes 2009) of bootstrap samples from the original sample to estimate the indirect effect (Preacher and Kelley 2011). The empirical distribution of these bootstrap estimates is then used to generate a confidence interval around the indirect effect (Hayes 2009). Bootstrapping is the most widely recommended method of choice for examining indirect effects (Preacher and Hayes 2004; Williams and MacKinnon 2008; Preacher et al. 2007). Compared to traditional methods for testing indirect effects such as the causal steps approach (Baron and Kenny 1986) or the Sobel test, bootstrapping demonstrates the "highest power and the best Type I error control" (Hayes 2009, p. 411).

We ran two sets of analyses to test our hypotheses. First, Table 3 shows the results of the mediation model, which tests the direct link between digital transformation and learning orientation (Hypothesis 1), the learning orientation and voice behavior (Hypothesis 2), and the indirect link between digital transformation and voice behavior via learning orientation (Hypothesis 3). Step 1 of Table 3 shows that, after accounting for the control variables, digital transformation positively and significantly related to employees' learning orientation ($B=0.17$, $p<0.05$), thereby supporting our Hypothesis 1. Step 2 of the table shows that learning orientation positively and significantly related to employees' voice behavior ($B=0.30$, $p<0.001$), providing support for Hypothesis 2. Moreover, the indirect effect of digital transformation on voice behavior via learning orientation (coeff.=0.05) was significant, as demonstrated by the finding that the confidence intervals for this coefficient did not include zero (CI [0.01; 0.13]). Thus, Hypothesis 3 received support. To assess whether this is a full or partial mediation, we additionally looked at the direct effect of digital transformation on voice behavior. This effect was not significant on a 5% level ($B=0.11$, $p=0.05$). We thus remain with the null hypothesis that this is a full mediation.

Table 3 Results of the mediation hypothesis (PROCESS, Model 4)

Step 1: Mediator variable model	Dependent variable: Learning orientation				
	Coeff	SE	Bootstrapped CI [95%]		<i>p</i>
			LL	UL	
					.18
Gender	.03	.25	– .47	.52	.92
Age	.00	.01	– .03	.02	.74
Education	.84	.25	.34	1.34	<.001
Fear of failure	– .01	.11	– .22	.20	.93
Industry	– .29	.25	– .78	.20	.24
Digital transformation	.17	.09	.00	.34	<.05
Step 2: Outcome variable model	Dependent variable: voice behavior				
	Coeff	SE	Bootstrapped CI [95%]		<i>p</i>
			LL	UL	
					.30
Gender	– .23	.15	– .53	.07	.14
Age	.00	.01	– .02	.01	.59
Education	.04	.16	– .28	.36	.81
Fear of failure	– .05	.16	– .17	.08	.48
Industry	.34	.15	.04	.64	<.05
Digital transformation	.11	.05	.00	.21	.05
Learning orientation	.30	.06	.17	.43	<.001
Direct effect of digital transformation on voice behavior	.11	.05	.00	.21	.05
Indirect effect of digital transformation on voice behavior via learning orientation	.05	.03	.01	.13	

N = 100, bootstrap sample size = 5000

LL lower limit, *UL* upper limit, *CI* confidence interval

Second, Table 4 shows the results for Hypothesis 4, which suggested that the above-noted mediation effect of digital transformation on voice behavior via learning orientation would be moderated by perceived surveillance. Step 1 of Table 4 shows that after accounting for the control variables and main effects, the interaction term between digital transformation and perceived surveillance had a negative and significant effect on learning orientation ($B = -0.15$, $p < 0.01$). In accordance with Hypothesis 4, the effect of digital transformation on learning orientation was weaker under high perceived surveillance.

We chose the Johnson–Neyman technique (Johnson and Neyman 1936)—a so-called floodlight analysis—to display this significant interaction effect, as shown in Fig. 2 (using the CAHOST tool by Carden et al. 2017). This technique identifies “regions in the range of the moderator variable where the effect of the focal

Table 4 Results of the moderated mediation hypothesis (PROCESS, Model 7)

Step 1: Mediator variable model	Dependent variable: learning orientation				
	Coeff	SE	Bootstrapped CI [95%]		<i>p</i>
			LL	UL	
					.28
Gender	-.02	.24	-.50	.46	.93
Age	-.01	.01	-.03	.02	.53
Education	.77	.24	.30	1.25	<.01
Fear of failure	-.02	.10	-.22	.19	.86
Industry	-.25	.24	-.72	.22	.29
Digital transformation	.16	.08	.00	.32	<.05
Perceived surveillance	-.23	.08	-.39	-.07	<.05
Digital transformation × perceived surveillance	-.15	.05	-.26	-.05	<.01
Step 2: outcome variable model	Dependent variable: voice behavior				
	Coeff	SE	Bootstrapped CI [95%]		<i>p</i>
			LL	UL	
					.30
Gender	-.23	.15	-.53	.07	.14
Age	.00	.01	-.02	.01	.59
Education	.04	.16	-.28	.36	.81
Fear of failure	-.05	.06	-.17	.08	.48
Industry	.34	.15	.03	.64	<.05
Digital transformation	.11	.05	.00	.21	.05
Learning orientation	.30	.06	.17	.43	<.001
Direct effect of digital transformation on voice behavior	.11	.05	.00	.21	.05
Conditional indirect effects of digital transformation on voice behavior via learning orientation					
Low perceived surveillance (1 <i>SD</i> below the mean)	.11	.04	.04	.21	
High perceived surveillance (1 <i>SD</i> above the mean)	-.02	.04	-.10	.07	
Index of moderated mediation	-.05	.02	-.09	-.01	

N = 100, bootstrap sample size = 5000

LL lower limit, *UL* upper limit, *CI* confidence interval

predictor on the outcome is statistically significant and not significant" (Matthes et al. 2010, p. 93). The dotted line in Fig. 2 shows the corresponding values of the simple slopes relating digital transformation to learning orientation (on the y-axis) for the values of the moderator (perceived surveillance; x-axis). The gray areas around the dotted line display the confidence bands for each point. For any value of the moderator (perceived surveillance) where the confidence bands contain zero, the effect of digital transformation on learning orientation is not

Fig. 2 Floodlight analysis. The association between digital transformation and learning orientation as a function of perceived surveillance. The dotted line indicates the simple slope of digital transformation on learning orientation. Shaded areas show the regions of significance (95% confidence interval)

significantly different from zero. For any value of the moderator where the confidence bands exclude zero, the effect is significantly different from zero. The Johnson–Neyman Point is the turning point “where exactly, in the absolute value of the moderator, the effect of the independent variable turns from non-significance to significance” (Krishna 2016, p. 332). In Fig. 2, the Johnson–Neyman Point is 2.25. Thus, when perceived surveillance is lower than 2.25, there is a significant (positive) effect of digital transformation on learning orientation. However, this effect turns into non-significance when perceived surveillance is higher than 2.25. This finding provides additional and more fine-grained support for Hypothesis 4 that digital transformation increases learning orientation, but only when perceived surveillance is low.

As suggested in our moderated mediation hypothesis, the interaction effect on learning orientation further transmits to voice behavior as a final outcome. Step 2 in Table 4 demonstrates that learning orientation related positively to employees’ voice behavior ($B=0.30$, $p<0.001$). Further support for Hypothesis 4 comes from looking at the conditional indirect effects—that is, the indirect effect of digital transformation on voice behavior via learning orientation at different values of the moderator, perceived surveillance (Preacher et al. 2007). Table 4 shows that under low perceived surveillance (1 *SD* below the mean), digital transformation leads to significantly higher voice behavior via enhanced learning orientation (coeff. = 0.11; CI [0.04; 0.21]). This significant positive indirect effect disappears and becomes insignificant (as indicated by the confidence interval including zero) when perceived surveillance is high (1 *SD* above the mean; coeff. = -0.02 ; CI

[− 0.10; 0.07]). Most importantly, we looked at the index of moderated mediation as a direct significance test for moderated mediation effects (Hayes 2015). As shown in Table 4, the index was significant, as indicated by confidence intervals excluding zero (index = − 0.05, CI [− 0.09; − 0.01], lending support to our Hypothesis 4. Altogether, the post-hoc effect size of our hypothesized model (including all hypothesized and control variables) was $f^2 = 0.35$, indicating a large effect according to Cohen's (1988) guidelines, and the obtained statistical power was high ($1 - \beta = 0.99$).

5 Discussion

Digitization forces organizations to be innovative (Frishammar et al. 2018). Firms striving for innovation depend on employees at all levels of the organizational hierarchy to be creative, to put forward innovative suggestions, and to actively support innovative ideas (Lee et al. 2018). In other words, nowadays, organizations cannot afford their employees to remain passive and silent. Our study sheds light on two important cornerstones of innovation in times of digital transformation—that is, employees' learning orientation and voice behavior.

On the one hand, our findings paint a positive picture of employee reactions to digital transformation. Supporting the assumption of self-determination theory (Deci and Ryan 1985), digital transformation encourages employees to engage in an intrinsically motivated process. In the sense of a discontinuous learning event (Cope 2003), digital transformation forces employees to critically question beliefs and assumptions that they have taken for granted. Digital transformation stimulates employees to tackle the challenges with a learning orientation, reflecting an intrinsically motivated approach to develop the skills and competencies needed to keep abreast of the novel requirements in the digital age. As an important outcome of the adopted learning orientation, employees are more likely to offer suggestions to improve the current state of affairs in their organizations, i.e., to show voice behavior.

On the other hand, our study also shows that employee surveillance via technology can cast a shadow on the positive effects of digital transformation on employees. That is, this positive, intrinsically motivated process is critically affected whenever employees feel that digital transformation goes along with increased surveillance of their daily work. In line with cognitive evaluation theory (Deci and Ryan 1985), surveillance undermines employees' feelings of autonomy and thereby hinders them to adopt an intrinsic learning orientation. Consequently, employees remain silent and refrain from making suggestions that could help their organization. Thus, when employees are too much in the spotlight of managerial control, their default and innate tendency to learn, develop, and improve their environment vanishes.

5.1 Theoretical implications

Our study contributes to three main literature streams. First, contributing to the digitization literature, our study illustrates that we cannot fully understand the pervasive effects of digital transformation without considering the employee perspective. The emerging stream of digitization research is characterized by three most prevailing theoretical perspectives to date—that is, a technology perspective (e.g., Shaheer and Li, *in press*, von Briel et al. 2018), a business model perspective (e.g., Tilson et al. 2010; Weill and Woerner 2013), and an entrepreneurship perspective (e.g., Autio et al. 2018; Nambisan 2017). We suggest that, in addition to the existing theoretical lenses, a psychology perspective to digital transformation is needed. In our sample, we find support for the idea that digital transformation influences firms on an employee level, since it radically changes work environments and routines (cf., Carter et al. 2013). Our findings show that digital transformation immediately affects employee learning and their likelihood to speak up. These outcomes are important also from an organization-level point of view, because learning and voice behavior are key roots of innovation and thus competitive advantage in the digital age (cf., Fuller et al. 2006). That way, our findings also support the view that whether or not an organizational change process turns out to be successful largely depends on employees' reactions to it (cf., Oreg et al. 2011).

Second, our study contributes to the innovation management literature, as it shows how digital transformation affects two inter-related central cornerstones of (digital) innovation—employee learning and employee voice behavior. Learning domain-relevant skills and knowledge is essential for employees, as it enables them to engage in creative and innovative thinking (Gong et al. 2009). However, unless employees proactively articulate their suggestions and ideas (i.e., engage in voice behavior), organizations cannot benefit from employees as a valuable source of bottom-up innovation (Guzman and Espejo 2018; Lee et al. 2016). Following Fuller and colleagues (2006: 1098), “understanding the process by which people choose to engage in voice behavior is critical if we are to gain a fuller understanding of the innovation process”. Our study is the first to show how digital transformation affects employees' choice to engage in learning and voice behavior. Supporting the perspective of self-determination theory, we find that digital transformation generally affects employee behavior positively. By default, digital transformation triggers an intrinsically motivated process that activates employees' learning behavior, which consequently motivates them to raise their voice. A popular view often raised in public media portrays many employees as being afraid of the changes related to digitization and digital transformation or even “technophobic” (Khasawneh 2018; Partington 2018). Our findings contradict this view, showing that the employees in our sample generally saw digital transformation as a learning opportunity, not as a threat. That way, the disruptive changes associated with digitization urge employees to dedicate themselves to acquiring the skills and competencies needed in the digital age. This in turn can benefit their own future professional careers.

Third, our study contributes to the managerial control and surveillance literature. The advancement of digital technologies facilitates managerial control by offering new opportunities to monitor employee behavior in the workplace (Stanko and

Beckman 2015). At the same time, Cardinal and colleagues (2017) have criticized that research in the domain of managerial control has not kept pace with the pervasive changes within modern work environments. In highlighting the importance of perceived surveillance in the context of digital transformation, our study offers important insights into this regard. Our findings support the view that perceived surveillance has a negative effect on employee reactions and behavior (cf., Holland et al. 2015), especially in a context related to innovation (Allen et al. 2015). Subsequently, our findings show that surveillance particularly counteracts learning and voice behavior when employees are simultaneously confronted with high digital transformation of their work environment. In such an exceptional situation, when individuals experience fundamental changes and high job demands (Van Knippenberg et al. 2015), they seem to react in a more sensitive way to perceived surveillance.

5.2 Practical implications

Our study delivers important insights for the management of organizations undergoing digital transformation. Around 70 percent of all corporate digital transformation programs fail to reach their goals and low employee engagement has been identified as one of the most common pitfalls (McKinsey 2018). Our study supports the notion that one key for successful digital transformation lies within a firm's employees. A workforce equipped with the required skills, knowledge, and expertise is crucial for business success and competitive advantage (Huselid 1995)—especially in times where digitization forces organizations to innovate (Maes and Sels 2014). However, many organizations currently lack the required human capital to successfully meet the challenges of digitization (OECD 2016). For strategic HR management, this results in a classic “make-or-buy” decision—organizations can increase human capital internally through training or externally by hiring talents from the job market (Lepak and Snell 1999). The “buy” option is often difficult against the background of the ongoing “digital war for talent” (Kane et al. 2017). The present study sheds a favorable light on the “make” option. Our findings indicate that there is a powerful potential within existing workforces—individuals' innate tendency to learn. In times of digital change, managers should foster and actively take advantage of employees' learning motivation. Learning new (digital) skills should become a part of employees' everyday work (Bersin and Zao-Sanders 2019). Moreover, peer-to-peer learning programs could be a useful strategy, since learning from colleagues within a safe learning environment has been described as a powerful way for developing skills and capabilities (Palmer and Blake 2018). We further recommend that HR management should support employee learning and voice behavior by offering training programs as well as opportunities to raise ideas and suggestions. Learning—as our findings suggest—transforms employees into mature and responsible actors who proactively spot rooms for improvement and consequently bring forward new innovative ideas.

At the same time, management should pay attention to our finding that perceived surveillance could undermine the beneficial process initiated by digital transformation. Managers are responsible for determining and shaping the job design and

thereby exert a decisive influence on the monitoring and surveillance of employee behavior (Allen et al. 2015). The findings of our study indicate that, especially in times of high digital transformation, organizations should carefully consider the implementation and the extent of surveillance via technology. Given that perceived surveillance undermines employees' natural tendency to engage in intrinsically motivated learning and voice behavior, organizations should—whenever possible—favor HR systems that foster employee autonomy and proactivity (Lee et al. 2016). A promising approach in this regard could be employee self-management, which builds on personal responsibility, autonomous decision-making, and trust (Jensen and Raver 2012). HR management should also consider the adverse effects of perceived surveillance on employees' learning orientation when designing training programs in the context of digital transformation. Following our findings, it could be helpful to refrain from close monitoring of training results (cf., Watson et al. 2013) in order to give employees the chance to follow their own, intrinsic learning orientation.

5.3 Limitations and future research directions

Despite the contributions of this research, several limitations need to be considered. First, our findings might be limited in generalizability. We have made efforts to anticipate this issue by testing our research model in two industry contexts that are significantly disrupted by digitization. However, even though we carefully chose these industries, they might not be representative for all industries undergoing digital transformation. We thus call for future research to replicate our findings in additional industries, including industries outside the German market (cf., Robinson 2011). Related to that, the individuals surveyed in this study might not be representative for all individuals experiencing digital transformation. We especially encourage scholars to examine the underlying assumptions of self-determination theory in further research contexts. Particularly, while the idea that employees perceive digital transformation as a valuable learning opportunity receives support in our sample, this might not be the case for all employees. The observed education difference for learning orientation indicates that not all employees might value learning equally. Likewise, personality differences (e.g., extraversion), differences in functional background, or the position within the firm might play a role, for which we did not control. Future research should thus further explore the factors that make individuals perceive digital transformation as a learning opportunity, as a necessary obligation, or even as a threat. It would be especially interesting to also identify extrinsic factors that strengthen (instead of undermine) the intrinsically motivated process, e.g., training programs provided by firms.

Second, future research should take a closer look at the potentially diverging effects of surveillance via technology. While the focus of our study was to explore employees' subjective perception of being monitored at work, we did not differentiate among various methods and contexts of electronic surveillance. However, surveillance can take different forms, for instance, software monitoring, video monitoring, or location monitoring. In addition, electronic monitoring in the workplace

is strictly regulated by legislation, which also varies by country (Nord et al. 2006). Whether or how these differences affect employees' reactions to surveillance via technology should thus be further explored. In addition, the use of a single item to capture perceived surveillance might not be ideal. We thus encourage future research to measure perceived surveillance with a multi-item measure.

Third, given that we collected all data from one source (i.e., employees), our findings might be subject to common method bias. Given that we were interested in employee perceptions of surveillance and digital transformation, as well as employee goal orientation and voice behavior, this approach seemed appropriate. In addition, our analyses did not raise concerns over common method variance. Nevertheless, the robustness of our findings could be demonstrated by using supervisor ratings of employee voice instead of self-ratings.

Fourth and finally, we have taken a cross-sectional approach to examining the effects of digital transformation on employee reactions. Given its complexity, digital transformation is naturally a long-term project for organizations. Future research should thus apply longitudinal study designs in order to examine how digital transformation affects employees over time.

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