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Technological Frames in the Digital Age: Theory, Measurement Instrument, and Future Research Areas

Patrick Spieth[a], Tobias Röth[a], Thomas Clauss[b] and Christoph Klos[a]

[a]*University of Kassel;* [b]*Private Universität Witten/Herdecke, University of Southern Denmark*

ABSTRACT Digital technologies fuel technological change that generates substantial uncertainty and complexity. Corporate actors rely on their technological frames to cope with these challenges. Technological frames determine how actors interpret, assess, and shape a technology's development, usage, and trajectory. However, the research fails to provide insights into the microfoundations that can explain the consequences of heterogeneity in technological frames. We argue that this research gap is due to a lack of a proper measurement instruments. To address this gap, we theorize on the antecedent of technological frames on the individual level and undertook a rigorous scale-development process encompassing five steps and samples. The resulting measurement instrument assesses five distinct but interrelated dimensions of an actor's technological frame (personal attitude, application value, organizational influence, industrial influence, and supervisor influence). This instrument provides a theoretical and methodological foundation for future research on technological frames and corporate strategizing in the digital age.

Keywords: digital technology, microfoundation, organizational change, scale development, technological frame, technology implementation

INTRODUCTION

Digital technologies, such as artificial intelligence, blockchains, cloud computing, and the Internet of Things, as well as the speed with which they are developed have foundationally changed products, services, operations, and business models (Chanias et al., 2019;

Address for reprints: Patrick Spieth, Full Professor of Technology, Innovation Management and Entrepreneurship, University of Kassel, Kleine Rosenstraße 3, 34117 Kassel, Germany (spieth@uni-kassel.de).

All authors contributed equally to this article.

Hanelt et al., 2021; Kumaraswamy et al., 2018; Vial, 2019). To develop suitable strategies that facilitate technology-induced organizational change, corporate actors need to interpret, assess, and select appropriate digital technologies (Bailey et al., 2010; Chanias et al., 2019; Furr et al., 2012).

However, the uncertainty and complexity of digital technologies make their interpretation and assessment challenging for several reasons. First, when actors encounter digital technologies for the first time, they are unsure about what they are, how they perform, against which criteria they should be judged, and how they will affect their business (Kaplan and Tripsas, 2008; von Krogh, 2018). Second, digital technologies create substantial complexity, as they extend objects' physical aspects by adding immaterial, abstract functionalities that enable new forms of collaboration and work practices between physical objects and/or actors (Bailey et al., 2010; Nambisan et al., 2017). To focus their attention on the relevant features of digital technologies, interpret their usefulness, and take action, actors rely on their cognitive, interpretive schemata, otherwise known as 'technological frames' (Cornelissen and Werner, 2014). Technological frames describe the assumptions, expectations, and knowledge that an actor uses to understand a technology's application and consequences in a particular context (Kaplan and Tripsas, 2008; Orlikowski and Gash, 1994).

The research focused on this issue fails to provide a comprehensive understanding of the variety of technological frames on the individual level and the consequences of heterogeneous technological frames on the collective level. This gap has two main causes. First, the literature does not offer a measurement instrument that can directly assess corporate actors' technological frames and, thereby, investigate variety in those frames on an individual level. Instead, researchers apply thematic content analysis, qualitative methodologies, and indirect proxies to assess the antecedents and consequences of technological frames (Cornelissen and Werner, 2014; Leonardi and Barley, 2010). Second, the literature mainly defines technological frames as a 'collectively constructed' phenomenon (Cornelissen and Werner, 2014, p. 185) and, thereby, neglects its multi-level nature (Kaplan and Tripsas, 2008). This is problematic, as we cannot understand the reasons for inconsistent findings on the consequences of (in-)congruent technological frames. On the one hand, congruency in technological frames among actors results in homogenous patterns of digital technology use, drives technology implementation, and facilitates organizational change (Azad and Faraj, 2008; Leonardi, 2011; Young et al., 2016). On the other hand, congruent technological frames can allow for heterogeneous technology use patterns (Mazmanian, 2013). Moreover, even inconsistent technological frames can be instrumental for cross-functional collaboration in innovation processes (Van Burg et al., 2014; Vaccaro et al., 2011), learning (Anthony, 2018; Seidel et al., 2020), and attracting supporters for disruptive innovations (Kumaraswamy et al., 2018).

In response, this study unpacks potential reasons for the heterogeneity in the collective consequences of technological frames. More specifically, we explore the theoretical underpinnings of variety in technological frames on an individual level and develop a measurement instrument as foundation for further research. We synthesized the technological frame literature and used an iterative, multi-step scale-development process that draws on five distinct samples to identify, purify, validate, and test our measurement instrument (DeVellis, 2016; Hinkin, 1995). The resulting instrument assesses actors' technological frames by differentiating among the dimensions of personal attitude, application value, organizational influence, industrial influence, and supervisor influence.

Our results expand the literature in two ways. First, the theorization and development of a scale on the individual level extend our knowledge of technological frames by providing insights into their microfoundations (Felin et al., 2015). Thereby, we synthesize the literature on different antecedents of technological frames into one construct that allows for assessment of variety in actors' technological frames (Cornelissen and Werner, 2014; Kaplan and Tripsas, 2008). Second, this study offers the methodological means to rigorously model and test actors' technological frames, interactions, and context influence outcomes (Hoppmann et al., 2020; Young et al., 2016). These theoretical and methodological means lay the foundation for a research agenda that encompasses the following research areas: *social interaction*, *heterogeneity in consequences*, and *management of technological frames*. Moreover, they point to specific research questions within these areas that can inform future studies focused on enhancing our understanding of corporate strategizing and technological frames in the digital age.

TECHNOLOGICAL FRAMES: THE LACK OF A COMPREHENSIVE UNDERSTANDING AND MEASUREMENT INSTRUMENTS

Corporate strategies differ considerably in their interpretation of and reactions to the new technologies. Researchers apply the technological frame concept to understand this heterogeneity (Kaplan and Tripsas, 2008). To develop theory on how technological frames vary on an individual level, we review two related research streams that are specific to the interpretation of technology: literature on the social construction of technology (Leonardi and Barley, 2010; Pinch and Bijker, 1984) and literature on technological frames (Cornelissen and Werner, 2014; Davidson, 2006). Both research streams offer valuable insights into the antecedents and consequences of technological frames.

Antecedents of Technological Frames

As Table I indicates, technological frames are rooted in actors' experiences and histories, their social affiliations within the corporation, and their industrial affiliations (Cornelissen and Werner, 2014; Kaplan and Tripsas, 2008; Leonardi and Barley, 2010).[1]

Actors' education, training, and personal experiences influence their meaning construction in relation to technologies (Leonardi and Barley, 2010; Pinch and Bijker, 1984; Schmitz and Fulk, 1991). For example, when consultants first implemented Lotus Notes, they drew on their experiences with other digital technologies, such as e-mail and spreadsheets (Orlikowski and Gash, 1994). The novel technology's characteristics functioned as a cue that activated a certain technological frame. According to this technological frame, the consultants interpreted Lotus Notes as a digital tool relevant only for individual tasks and disregarded its collaboration potential. Thus, actors' individual experiences with more or less comparable technologies shape their meaning construction in relation to novel technologies (Davidson, 2006; Young et al., 2016).

Actors' social affiliations with colleagues also shape their meaning construction in relation to new digital technologies (Bijker, 1995; Fulk, 1993). For instance, Pinch and Bijker

Table I. Research on technological frames and related research on technological artefacts

Articles	*Measurement of technological frames*	*Antecedences*	*Contextual influences*	*Consequences*
Orlikowski and Gash (1994)	Case-study research: inductive coding of interviews, observations, and archival data	Socially constructed; dimensions of technological frame: • Nature of technology • Technology strategy • Technology in use		• Technology development • Technology usage patterns • Technology-induced change
Bijker (1995)	Analysis of historical data	Interaction between relevant social groups: • Interpretative flexibility • Technological frame closure • Technological frame stabilization	Power conflicts	• Technology development • Technology trajectory
Davidson (2002)	Case-study research: inductive coding of interviews, team meetings, observations, and archival data	Four technological frame domains: • IT delivery strategies • IT capabilities and design • Business value of IT • IT-enabled work practices	• Formal power • Informal (interpretative) power	Development and implementation of technologies: reoccurring shifts in frame salience caused repeated reinterpretations of the technological artefact and its requirements
McGovern and Hicks (2004)	Case-study research: inductive coding of field notes from, observations, and archival data	• Type of partnership • Nature of technology • Technology structure • Technology in use	• Formal power • Political processes	Technology implementation
Allen and Kim (2005)	Thematic content analysis of historical data	• Use vision • Industry practices • Technology performance		• Technology usage patterns • Technology trajectories
Azad and Faraj (2008)	Case-study research: inductive coding of interviews and archival data	• Frame differentiation • Frame adaptation • Frame stabilization	• Power balance • Internal political behavior • External events	Negotiated truce frame that guides technology implementation
Kaplan and Tripsas (2008)	None; conceptual and theoretical	Interactions of: • Producers • Users • Institutions	Technology life cycle	Technology trajectories: uncovering intertemporal interactions among multiple actors' framing, collective technological frames, and technology trajectories

Table I. *Continued*

Articles	*Measurement of technological frames*	*Antecedences*	*Contextual influences*	*Consequences*
Mishra and Agarwal (2010)	Cross-sectional survey: three latent constructs; each construct is operationalized using four to six items	Interpretation of technological artefact in terms of a: • Benefits frame • Threat frame • Adjustment frame	Organizational capabilities: • Technological opportunism • Technological sophistication	Technology usage
Leonardi (2011)	Case-study research: inductive coding of interviews and archival data	Technology concepts shape frames around cultural resources that guide actors' problem-construction practices	Actors' affiliations with a social group	Cross-functional collaboration in new product development
Vaccaro et al. (2011)	Case-study research: inductive coding of interviews, observations, and internal and external archival data	• Technological competencies • Strategic objectives • Complementary assets	Granularization of the design space/degree of modularization (e.g., how the design space is divided into components and subcomponents)	Development of knowledge in new product development
Furr et al. (2012)	Analyses of panel data: top management team members' expertise operationalized as proxies assessing their industry affiliations and other biographical data	• Domain insider • Domain outsider • Complementary		Degree of technology change in the venture's product portfolio
Mazmanian (2013)	Case-study research: inductive coding of interviews, observations, and internal and external archival data	Reframing of technologies: • Occupational identity • Materiality • Vulnerability to social pressure • Visibility of communication acts		Heterogeneity of technology usage patterns within a user group
Olesen (2014)	Case-study research: inductive coding of interviews, observations, and internal and external archival data	Social interaction within a group of actors determining the content of a technological frame	Formal power	• Technology implementation • Technology usage patterns

Table I. *Continued*

Articles	*Measurement of technological frames*	*Antecedences*	*Contextual influences*	*Consequences*
Van Burg et al. (2014)	Case-study research: inductive coding of interviews, historical narratives, and internal and external archival data	Events trigger (re-)framing: • Threat • Opportunity	• Evolving relational context (prior relationships and contractual governance mechanism) • Developing knowledge base (accumulated stock of tacit knowledge and formal appropriability)	Interorganizational knowledge transfer that (intertemporally) can shape the context
Young et al. (2016)	Case-study research: inductive coding of interviews, field notes, and internal and external archival data	Inconsistencies and incongruences: • Between and within different groups • Within the technological frame (nature of technology, technology strategy, and technology in use)	• Market, technological, and competitive turbulence • Internal reorganization	• Technology implementation • Technology-induced organizational change
Anthony (2018)	None; conceptual and theoretical	Interpretation as: • Threat • Opportunity	Salience of status differences: the influence of status differences on the interaction of actors	Acceptance or questioning of the technology's output and its effects on the novelty of knowledge outcomes
Kumaraswamy et al. (2018)	None; conceptual and theoretical	Framing practices of disruptive innovations: • Threat • Opportunity		Heterogeneity of the responses to disruptive innovations among actors within an ecosystem
Hoppmann et al. (2020)	Case-study research: inductive coding of interviews, and internal and external archival data	• Framing dimensions (potential, prospect, performance, progress) • Framing tactics (conclusion, conditioning, concession)	Technology life cycle: • Technology maturity • Technology evolution	Technology hypes
Seidel et al. (2020)	None; conceptual and theoretical	Exchange of rumors and propositions among consumers, producers, and other actors		Development of technologies and new products

(1984) show that different actors are affiliated with specific social groups, and that distinct social groups can have radically different interpretations of a technology's purpose and usefulness. At the same time, corporate actors influence each other in their daily work and, thereby, construct and deconstruct the social reality surrounding technological artefacts (Hoppmann et al., 2020; Vaccaro et al., 2011).

In addition, corporate leaders' unique hierarchical position and status influence meaning construction among their followers (Anthony, 2018; McGovern and Hicks, 2004; Olesen, 2014). For instance, founders imprint their unique cognitive perspectives and interpretations into the corporations even when members of that organization lack a shared history (Beckman, 2006; Furr et al., 2012). Moreover, leaders of incumbent firms can provide a technological frame that stimulates, dominates, and overrides their followers' interpretations of novel technologies (Davidson, 2002; Schmitz and Fulk, 1991).

Actors' affiliations outside the corporation also affect the way in which they construct meaning in relation to a new technology (Kaplan and Tripsas, 2008; Van Burg et al., 2014). For instance, in periods of relative stability, corporations within the same industry typically develop shared cognitive templates that shapes actors' common understanding of a specific technology. However, this shared understanding can collapse in periods of rapid technological change, thereby causing divergent interpretations of novel technologies (Allen and Kim, 2005; Kaplan and Tripsas, 2008; Kumaraswamy et al., 2018). Thus, corporate actors' associations with competitors, customers, and suppliers substantially influence their technological frames (Kaplan and Tripsas, 2008).

Consequences of Technological Frames

While the research identifies the antecedents of technological frames on an individual level, their effects on technology development, usage, implementation, and trajectories are mainly investigated collectively (Bijker, 1995; Hoppmann et al., 2020; Kaplan and Tripsas, 2008; Leonardi, 2011; Mazmanian, 2013; Orlikowski and Gash, 1994; Seidel et al., 2020). However, the literature fails to explain the heterogeneity in the specific consequences of technological frames given their variety on the individual level.

Of the different consequences, this study explores the variety in individual reactions to new digital technologies implemented by corporations. When actors are confronted with a novel digital technology, they draw on their technological frames to interpret that technology and make sense of its consequences (Leonardi and Barley, 2010; Orlikowski and Gash, 1994). Technological frames function as interpretive principles through which actors reduce a technology's complexity, direct their attention to its focal features, and organize and assign meaning to that technology (Kaplan and Tripsas, 2008; Orlikowski and Gash, 1994). As such, technological frames shape the valence that an individual assigns to a specific technology (i.e., the actor's evaluation of a technology's attractiveness) (Dutton and Jackson, 1987; Plambeck and Weber, 2010).

As digital technologies can create new interdependencies between technologies and/or actors and replace existing ones, their implementation can lead to substantial organizational change (Anthony, 2018; Bailey et al., 2010; Mazmanian, 2013). When faced with such a technology-induced change, actors can either resist or accept it. These reactions reflect their attitudes towards change and their affective commitment, which, in turn, influence the efficiency and effectiveness of the technology's implementation (Cornelissen and Werner, 2014; Vial, 2019).

Given that an actor's technological frame shapes his or her interpretation of technology-induced change (Davidson, 2006; Young et al., 2016), that frame is likely to affect his or her attitude towards the change itself. This attitude involves the actor's perception of, affective reaction to, and behavioural tendency towards the change (Dunham et al., 1989). When an actor interprets digital technology-induced change as unattractive (i.e., negative valence), political contestation, conflicts, and open questioning of the technology's outcomes are likely (Anthony, 2018; Orlikowski and Gash, 1994; Young et al., 2016). When an actor's interpretation is positive, he or she is likely to recognize that technology's advantages, and be more confident and optimistic about the resulting organizational changes (Oreg et al., 2011).

Moreover, as digital technologies can alter actors' tasks, work environments, and roles (Anthony, 2018; Bailey et al., 2010), they are likely to influence actors' affective commitment. 'Affective commitment' describes the mindset that binds an actor to a course of action oriented towards certain targets (Herscovitch and Meyer, 2002). In particular, actors perceive new digital technologies as change accelerators, and they begin to imagine the organizational-change process and their respective roles in it. When an actor's technological frame results in a positive interpretation of a digital technology (i.e., positive valence), that actor perceives the technology as potentially useful for his or her daily work (Meyer and Allen, 1997). This perception is likely to enhance the actor's commitment to the corporation. In contrast, when an actor interprets a digital technology as unattractive (i.e., negative valence) because it may increase the complexity of a task or even impede its execution, the actor's affective commitment is likely to be lower.

Previous Approaches to Measuring Technological Frames

Approaches to measuring technological frames are grounded in research on strategic management (Cornelissen and Werner, 2014; Kaplan, 2011) and the social construction of technology (Leonardi and Barley, 2010). Instead of operationalizing technological frames as a latent construct, the research mainly applies thematic content analysis, qualitative analysis, and biographical proxies.

Thematic content analysis focuses on actors' beliefs, interpretations, and understandings (Cornelissen and Werner, 2014). These approaches typically code the meaning of words, slogans, catchphrases, and metaphors found in internal and archival data. They are usually bound to a digital technology's specific organizational, technological, and institutional circumstances (Davidson, 2006).

In an attempt to overcome this drawback, qualitative research inductively analyses interview data and archival sources to investigate the social interactions that construct and shape technological frames. This empirical perspective is either based on an ethnographic tradition of grounded theory approaches (e.g., Leonardi, 2011; Mazmanian, 2013) or applies a multiple case-study research design (e.g., Hoppmann et al., 2020). However, as these measurements are embedded in their natural contexts, they require further validation.

Another methodological approach utilizes proxies that assess an actor's background with the aim of offering generalizable results (Kaplan, 2011). For instance, Furr et al. (2012) measure executives' industry affiliations and other biographical data to predict how they frame technological change. However, these approaches do not directly assess technological frames. Instead, the concept of technological frames functions as a theoretical explanation that acts as a mediator between individual proxies and strategic choices.

A few studies directly assess technological frames as latent constructs. Mishra and Agarwal (2010) differentiate among benefit frames, threat frames, and adjustment frames, and operationalize these constructs as multi-item measurements. However, their context-sensitive operationalization is tailored to capturing market-related interpretations that disregard the technology-centered perspective of technological frames. In contrast, Schmitz and Fulk (1991) and Fulk (1993) measure the richness and usefulness of digital communication technologies by assessing the social influence of colleagues on actors and experience of actors. In contrast to a technological frame, this approach focuses on the perception of a specific technology in order to understand its subsequent use patterns (Leonardi and Barley, 2010). Moreover, this operationalization neglects the affiliation of actors with the industry (Kaplan and Tripsas, 2008). In addition, it relies on abstract, single-item measures that are outperformed by multiple items (DeVellis, 2016). Notably, none of these latent constructs were developed using explicit scale-development procedures.

SCALE DEVELOPMENT

We followed a step-by-step process to develop a reliable and valid scale for measuring technological frames. We utilized Churchill's (1979) scale-development process, which we complemented with inductive and deductive item creation and purification (Hinkin, 1995). This process included four steps to develop the scale and an additional one to confirm nomological validity of the scale (see Figure 1).

We decided to examine the craft and construction industry because this industry is in the beginning of its technology lifecycle (European Commission, 2018). In such contexts, actors face substantial uncertainty and complexity as they interpret and assess digital technologies (Anthony, 2018; Bailey et al., 2010; Kaplan and Tripsas, 2008). In this industry, substantial degrees of manual labour, physical products, and physical manifestations of services characterize value creation. Consequently, craftspeople are likely to have

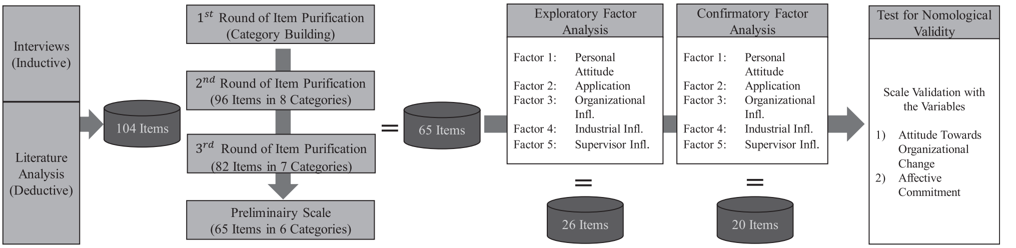

Figure 1. Scale-development process

limited experience with digital technologies, and they are likely to be unsure about their properties, performance, and effects on the corporation. Moreover, digital technologies, such as augmented reality or additive manufacturing applications, create complexity because often affect partnerships and daily tasks. Therefore, actors in the craft and construction industry are likely to draw on their technological frames when they face digital technologies. While executing the research steps, we continually used samples from the same industry to ensure internally consistent results. In contrast, the use of samples from different industries would have induced systematic differences in the antecedents of technological frames.

Stage 1: Item Generation and Initial Selection

We generated items using a combination of deductive and inductive approaches (Hinkin, 1995) in order to openly and comprehensively establish a technological frame's facets (Churchill, 1979). We based the initial item pool on the literature and existing instruments for measuring actors' initial reactions to technologies (DeVellis, 2016). In keeping with our theorizing on the antecedents of technological frames, we captured individuals' general attitudes towards technology and their expectations regarding its performance. We also captured individuals' previous experiences with technologies and their affiliations within their social systems.

To ensure that the theoretically derived dimensions validly captured the construct of technological frames, we conducted five initial interviews with practitioners from different firms. The interviewees had recently been confronted with new digital technologies and/or were in the process of integrating digital technologies into their operations (DeVellis, 2016). To validate the construct's domain, we provided the interviewees with the definition of technological frames and asked them to elaborate on their usual perceptions of new technologies. We then mirrored these descriptions with the categories of technological frames. As the interviewees also discussed their perceptions of their efforts to use and adopt new digital technologies, we added this category to our search for initial measurement items.

Two of the authors independently screened the literature on technological frames for items relevant for measuring their dimensions. To identify attitudes towards digital technologies, we utilized measurement items from Davis et al.'s (1992) scales regarding attitude towards behaviour and intrinsic motivation in relation to technology. We also used Thompson et al.'s (1991) and Compeau et al.'s (1999) measures of the effects of using new technologies. To capture the technology's expected performance, we included items from measures of performance expectations (Compeau et al., 1999; Davis, 1989) and technology job fit (Thompson et al., 1991). We captured expectations regarding the effort of using a technology through items focused on the ease of use (Davis, 1989) and perceived technological complexity (Thompson et al., 1991). Consequently, our initial item list comprised 46 items that we adapted to the digital technology context.

As previous survey research has not provided measures of experiential and social system influence (i.e., leader, organization, and industry), we used descriptions and explanations of these aspects found in the literature to develop a set of statements. In this regard, we derived the items expected to capture social influences on technological frames from

Davidson (2002), Furr et al. (2012), and Young et al. (2016). This led to the development of 13 items focused on capturing the influence of experience on technological frames, 11 items capturing supervisors' influence, 13 items measuring the organization's influence, and eight items measuring the industry's influence.

We then invited six experienced practitioners from different firms to participate in two qualitative focus groups and discuss the derived items. Two of the authors moderated and documented the focus groups. At the beginning of each focus-group discussion, the facilitator described the challenges of implementing digital technologies as well as opportunities to do so. The facilitator then asked the participants to share their opinions. During the group discussions, participants were given a detailed description of a digital technology (i.e., a digital learning tool), after which they were introduced to the measurement items on our initial list. We then asked them to discuss the items and reflect on whether they captured their perceptions when dealing with new digital technologies in general and the presented technology in particular. We concluded that the list captured the essential aspects of their mental templates, although we added a few statements that described the job-relatedness of the digital technology. This led to an initial pool of 104 potential items.

Stage 2: Item Purification and Sorting Procedure

64 experts from academia and practice developed individualized categories to assess the validity and initial inter-rater reliability of the 104 items for measuring technological frames (DeVellis, 2016). These experts included 40 industry professionals from three different firms, 9 professors, and 15 PhD students from three German universities. They were randomly assigned to four rounds of sorting tasks (see Table II),[2] during which they had to assign the items to categories while assessing their reliability and eliminating those that did not validly represent a category. We removed items that more than 10 percent of our experts did not assign to a category.

Three measures of inter-rater reliability were applied for each round of sorting (Tables III and IV): (1) Krippendorff's alpha (α_{CR}), which is a measure of inter-rater reliability that can be compared across different scales; (2) Fleiss's kappa (κ_{FL}), which allows for an analysis of the inter-rater reliability of more than two raters (DeVellis, 2016); and (3) item-placement ratios, which show the percentage of correctly placed items per category.

Participants were not given the category names and the categories were not explained. Instead, the participants had to define the categories after reading each item prior to the

Table II. Assignment of raters across sorting rounds

Raters	*Round 1*	*Round 2*	*Round 3*	*Round 4*
Professionals	6	8	11	15
Professors	2	3	2	2
PhD Students	1	3	6	5

Table III. Inter-rater reliability

Sorting Characteristics	*Round 1*	*Round 2*	*Round 3*	*Preliminary Scale*
Raters	9	14	19	22
Categories	9	8	7	6
Items	104	96	82	65
Krippendorf's alpha	0.41	0.64	0.80	**0.93**
95% confidence interval	0.36–0.46	0.60–0.68	0.77–0.84	0.90–0.95
Bootstrapping sample	10,000	10,000	10,000	10,000
Fleiss's kappa	0.45	0.56	0.68	**0.89**
95% confidence interval	0.43–0.46	0.55–0.57	0.67–0.70	0.88–0.90

Table IV. Agreement measures

Placement Ratio	*Round 1*	*Round 2*	*Round 3*	*Preliminary Scale*
Personal attitude	63%	65%	82%	96%
Personal benefit	22%	22%	–	–
Private use	22%	–	–	–
Organizational influence	74%	57%	87%	92%
Industrial influence	79%	70%	87%	96%
Application value	53%	64%	76%	90%
Experiences with digital technologies	55%	84%	81%	94%
Influence of the team	82%	80%	93%	–
Influence of the supervisor	78%	92%	93%	96%
Average	60%	67%	86%	94%

sorting process. However, the participants were allowed to adapt their categories after explaining their reasons for doing so. We then selected the most frequently mentioned categories and, together with the participants, developed definitions of them. The first sorting round exhibited comparatively low inter-rater reliability (α_{CR}=0.41, κ_{FL}=0.445) with an initial average item-placement ratio of 60 percent. Based on the item placement and discussions with our participants, we moved eight items associated with the 'private use' category to the 'personal attitude' category. We also reworded and refined several items before starting the next sorting round. In the second sorting round, we provided participants with definitions of each of the remaining construct categories. They were also allowed to place items into a 'not allocable' category (Netemeyer et al., 2003). In the third round, we repeated the item-purification process until we achieved good inter-rater reliability (α_{CR} = 0.93, κ_{FL}= 0.89, overall placement ratio = 94 percent). The final round confirmed six construct categories and a total of 65 items (see Table V). During the

Table V. Categories and number of items

Category	*# of Items*	*Category*	*# of Items*
Personal attitude	6	Organizational influence	12
Experience with digital technologies	15	Industrial influence	9
Application value	12	Influence of the supervisor	11

sorting process, we eliminated two of the initial round-one categories that could not be clearly distinguished from the others and only contained a few items. More specifically, 'private benefit' was merged with 'application value' and 'team influence' was merged with 'organizational influence'.

Stage 3: Exploratory Factor Analysis and Item Reduction

We conducted an exploratory factor analysis (EFA) to test the constructs' structure (DeVellis, 2016). To do so, we selected potential respondents from a database of 2,900 firms belonging to the Chamber of Crafts (*Handwerkskammer*) in the German states of Hessen and Saarland. This list is representative of the industry, as craft and construction corporations in Germany are required to be members of this organization. After manually eliminating micro enterprises (< 10 employees)[3] and firms not directly affected by digitalization (e.g., barber shops), 523 firms remained. We subsequently contacted these firms, described our study's purpose, and asked them to participate. A total of 47 firms (9 percent) agreed and were provided with a link to our online survey. After two reminders, we received a total of 114 individual responses from these firms.[4] After we screened these responses, we deleted six with extensive amounts (> 10 per cent) of missing data.

At the start of the survey, each respondent was provided with a description of the digital learning tool used, which ensured that all respondents had a similar understanding of the technology. Thereafter, the respondents rated their agreement with the 65 items using a seven-point Likert scale ranging from (1) strongly disagree to (7) strongly agree.

We ran a principal component analysis with varimax rotation for all 65 items to explore the factor structure. A Kaiser-Meyer-Olkin value of 0.889 and a significant ($p < 0.001$) Bartlett's test indicated that our dataset was appropriate for an EFA. We deleted items showing factor loadings of less than 0.6 or cross-loadings of more than 0.5 (Hair et al., 2016). This led to a final EFA solution with the 26 remaining items loading on five factors. This solution explained 81.1% of the total variance. We examined the corrected item-to-total correlation and Cronbach's alphas to assess our solution's reliability. The Cronbach's alphas of each factor ranged from 0.85 to 0.92, placing them above the common threshold of 0.7 (Cortina, 1993). The EFA replicated and further specified the expected factors regarding personal attitude, application, organizational influence, industrial influence, and supervisor influence. The EFA did not reproduce the category of experiences with new technologies, as these items were mixed in with those capturing general attitudes towards digital technologies. Table VI presents the EFA's results.

Table VI. EFA – rotated component matrix

#	Item	*Factor* 1	2	3	4	5
PA_1	My attitude towards digital technologies is positive	0.83				
PA_4	I have high expectations of digital technologies	0.81				
PA_6	I regularly buy digital technologies for myself	0.81				
PA_2	Digital technologies are an important part of my life	0.79				
PA_5	I regularly try to obtain information about digital technologies	0.77				
AP_4	Digital technologies make it possible to work more freely		0.83			
AP_5	Digital technologies could facilitate the coordination of my work tasks		0.81			
AP_3	Digital technologies make my work more flexible		0.74			
AP_8	Digital technologies reduce the possibility of making mistakes during work		0.74			
AP_6	Digital technologies improve my work		0.73			
AP_7	Digital technologies increase the effectiveness of my work steps		0.68			
OI_6	My colleagues remind me to use digital technologies for my job			0.86		
OI_8	My colleagues regularly recommend digital technologies to me			0.81		
OI_5	My colleagues demand that I use digital technologies for my job			0.77		
OI_7	My colleagues help me use digital technologies for my job			0.75		
II_7	Our competitors demand the use of digital technologies				0.85	
II_8	Our competitors successfully use digital technologies				0.83	
II_5	Our customers demand the use of digital technologies				0.75	
II_6	Our suppliers demand the use of digital technologies				0.74	
II_1	In our industry, digital technologies are used intensively				0.60	
SI_4	My supervisor quickly recognized the advantages of digital technologies					0.89
SI_7	My supervisor is willing to integrate digital technologies into the firm					0.87
SI_9	My supervisor asks me to use digital technologies					0.87
SI_3	My supervisor regularly speaks about digital technologies					0.87
SI_8	My supervisor is willing to dissolve existing structures to ensure the use of digital technologies					0.86
SI_6	My supervisor is an expert in the handling of digital technologies					0.84

Stage 4: Confirmatory Factor Analysis and Measurement Validation

We confirmed the factor structure using confirmatory factor analysis (CFA). Our final reflective constructs were personal attitude, application value, organizational influence, supervisor influence, and industrial influence. Consistent with our theory, we view these constructs as the common antecedents of technological frames that inform the dimensions of the technological frame construct. Therefore, our measurement instrument is a reflective-formative higher-order construct type II (Hair et al., 2016) consisting of five lower-order components (dimensions): personal attitude, application value, organizational influence, industrial influence, and supervisor influence. The lower-order components are in a formative relationship with the higher-order technological frame construct. Thus, the lower-order components (all five dimensions) are correlated from a methodological perspective and each dimension captures a specific, theoretically derived aspect of the domain of technological frames. The combination of the dimensions determines the meaning and, therefore, the measurement of the construct. In contrast, each lower-order component is measured using reflective items, where each item mirrors the respective dimension.

Given the reflective-formative nature of the higher-order construct, a change in one dimension does not necessarily imply a change in another. For instance, an industry might utilize a specific digital technology in its operations even though a certain corporate actor does not interpret that technology as useful and, subsequently, resists its implementation, thereby leading to different patterns of technology use (Cornelissen and Werner, 2014; Young et al., 2016).

We tested this theoretical model's reliability and validity using partial least squares (PLS) structural equation modelling in which we applied SmartPLS 3 and specified the model by means of a repeated indicator approach (Hair et al., 2016). We chose PLS due to its proven robustness (a result of its constant use in strategic management research (Hair et al., 2013)) and because covariance-based structural-equation models cannot model constructs with formative indicators at any level (Becker et al., 2012).

We developed a new questionnaire comprising the 26 items remaining after the EFA. This survey followed the same data-collection procedure as the one for the EFA but it was distributed to different sample of practitioners. A total of 224 questionnaires were returned (7.72% response rate). Nineteen responses with extensive amounts (>10%) of missing data were removed, leaving us with 205 usable responses for the CFA (7.07% per cent response rate). We applied nonparametric bootstrapping with 5,000 replications to obtain the standard errors for our structural model testing (Hair et al., 2013).

To assess the reliability and validity of our first-order reflective constructs, we tested their indicator reliability (IR), composite reliability (CR), convergent validity, and discriminant validity by following the common threshold values specified by Hair et al. (2013) (see Tables VII and VIII). All 20 indicators showed highly significant ($p < 0.001$) factor loadings, with their respective constructs ranging from 0.842 to 0.911. All IR values exceeded the recommended cut-off of 0.4. The CR values ranged from 0.915 to 0.953, thereby exceeding the threshold of 0.6. Convergent validity was established with the average variance extraction (AVE) ranging between 0.51 and 0.82 (above the cutoff of 0.5). As each squared AVE value exceeded the highest inter-construct correlations,

Table VII. CFA – first-order reflective constructs

Construct	#	*Item*	*Mean*	*Std. Dev*	*Loading*	*t-value*	*VIF*
Personal Attitude *α = 0.91* *CR = 0.95* *AVE = 0.79*	PA_1	My attitude towards digital technologies is positive	5.59	1.48	0.89	41.69	3.32
	PA_4	I have high expectations of digital technologies	5.16	1.57	0.91	70.39	3.33
	PA_2	Digital technologies are an important part of my life	5.54	1.41	0.89	44.63	2.83
	PA_5	I regularly try to obtain information about digital technologies	4.86	1.58	0.88	54.83	2.71
Application Value *α = 0.91* *CR = 0.93* *AVE = 0.78*	AP_5	Digital technologies could facilitate the coordination of my work tasks	4.80	1.70	0.90	67.56	3.13
	AP_3	Digital technologies make my work more flexible	5.03	1.55	0.87	47.78	2.45
	AP_8	Digital technologies reduce the possibility of making mistakes in my work	4.55	1.59	0.85	38.25	2.31
	AP_7	Digital technologies increase the effectiveness of my work steps	4.79	1.64	0.91	75.31	3.18
Organizational Influence *α = 0.89* *CR = 0.92* *AVE = 0.75*	OI_6	My colleagues remind me to use digital technologies in my job	3.62	1.53	0.86	32.89	2.44
	OI_8	My colleagues regularly recommend digital technologies to me	3.31	1.53	0.84	38.14	2.17
	OI_5	My colleagues demand that I use digital technologies for my job	3.80	1.56	0.89	51.56	2.66
	OI_7	My colleagues help me use digital technologies for my job	3.94	1.63	0.86	38.71	2.27
Industry Influence *α = 0.88* *CR = 0.92* *AVE = 0.73*	II_7	Our competitors demand the use of digital technologies	3.99	1.72	0.88	40.10	2.92
	II_8	Our competitors successfully use digital technologies	4.16	1.57	0.89	54.31	3.09
	II_5	Our customers demand the use of digital technologies	4.04	1.56	0.84	36.20	2.01
	II_6	Our suppliers demand the use of digital technologies	4.33	1.53	0.80	25.63	1.87
Supervisor Influence *α = 0.93* *CR = 0.95* *AVE = 0.81*	SI_7	My supervisor is willing to integrate digital technologies into the firm	4.84	1.75	0.91	68.39	3.38
	SI_9	My supervisor requests that I use digital technologies	4.41	1.77	0.91	75.64	3.35
	SI_3	My supervisor regularly speaks about digital technologies	4.24	1.77	0.90	57.05	3.14
	SI_6	My supervisor is an expert in the handling of digital technologies	3.95	1.76	0.89	46.17	2.87

Table VIII. CFA – inter-correlations and discriminant validity

	Application Value	*Industry Influence*	*Organizational Influence*	*Personal Attitude*	*Supervisor Influence*
Application value	**0.88**				
Industry influence	0.60	**0.86**			
Organizational influence	0.61	0.55	**0.86**		
Personal attitude	0.67	0.43	0.54	**0.89**	
Supervisor influence	0.64	0.45	0.59	0.60	**0.90**

Note: Numbers on the main diagonal show the square-root of the AVE.

Table IX. CFA – second-order formative construct

Second-order construct	*First-order construct*	*Weights*	*t-value*	*VIF*
Technological frame	Personal attitude	0.25	21.08	2.03
	Application value	0.27	25.91	2.66
	Organizational influence	0.24	21.17	1.95
	Industry influence	0.21	17.67	1.71
	Supervisor influence	0.26	22.17	2.01

discriminant validity was established according to the Fornell-Larcker criterion (Fornell and Larcker, 1981). In a more conservative test of discriminant validity, we calculated the heterotrait-monotrait ratio of correlations (HTMT) and the HTMT inference criteria for all first-order constructs. All HTMT values were below the threshold of 0.85, and all HTMT inference criteria were significantly different ($p < 0.05$) from 1 (Henseler et al., 2015).

To evaluate the formative measurement models (Table IX), we calculated the measurement weights of the first-order reflective constructs on the second-order formative technological frames construct, all of which were significant ($p < 0.001$). We also assessed potential multicollinearity between the first-order reflective constructs. As the variance inflation factors (VIFs) ranged from 1.706 to 2.656 and were below the conservative threshold of 5, multicollinearity did not appear to be an issue (Hair et al., 2013).

SCALE VALIDATION: TEST OF NOMOLOGICAL VALIDITY

In the next step, we established the new measurement instrument's nomological validity. This describes the degree to which the focal construct – a technological frame – relates to previously established relationships among other theoretically connected constructs (Hair et al., 2016). We, therefore, tested whether our construct could replicate findings on the effects of positive technological frames uncovered using other methods (Netemeyer et al., 2003). Consequently, we selected two constructs shown to be positively related to positive technological frames in the research. More specifically, we tested the associations between technological frames and two exemplary consequences: (1) attitudes towards change and (2) affective commitment to the firm.

Method

We specified a structural equation model in which our new measure of technological frames was used as an antecedent, and attitudes towards change and affective commitment were specified as consequences. We tested this model with SmartPLS 3, relying on the same model specifications as with the CFA.

Sample

We collected a large-scale, survey-based dataset for this final validation step. Prior to the main data collection, the questionnaire was pretested with a group of academics (n = 8) and practitioners (n = 7) to certify its quality. We sampled the same industry to ensure the internal validity of our results and we introduced the participants to the same technology as in the other studies. Our data were gathered by a professional data-collection firm that draws on a sample of 936 craft and construction firms. The participants were recruited in accordance the representative gender distribution, average age, and education of the German and Austrian craft and construction sectors (European Commission, 2018). We received of a list of 612 participants fitting the quota-sampling strategy, and we sampled 604 responses (64.52 per cent response rate) from December 2018 to January 2019. We checked them for uniform response styles by calculating each participant's standard deviation over all of the items. Questionnaires with an overall standard deviation of 0 were deleted. We also identified and deleted multivariate outliers using Mahalanobis distance values, resulting in a final dataset of 573 questionnaires (61.22 per cent final response rate). The sample consisted of 194 (33.9 per cent) women and 379 (66.1 per cent) men, ranging from 16 to 65 years of age with an average age of 41. Of the participants, 22.3 per cent were digital natives (i.e., younger than 35 years), while 77.7 per cent were digital immigrants.

We analysed the sample for potential survey biases. First, we tested for potential non-response bias by conducting a two-sample t-test, which confirmed that the answers from the early 25 per cent of respondents did not differ significantly from those of the late 25 per cent of respondents (Armstrong and Overton, 1977). Second, we addressed the potential for common method bias by considering common ex-ante design criteria to ensure the survey responses' validity, such as respondents' anonymity and the mixed presentation of the constructs in the survey (Podsakoff et al., 2003). In addition, we tested the influence of two perceptual marker variables not theoretically related to any of our model constructs (Lindell and Whitney, 2001) using two single-item measures: (1) 'I could easily get a job in a better position' and (2) 'My working hours vary from day to day'. After separately partialling out each of these marker variables, we detected only minimal changes in the size of our variables' zero-order correlations ($\Delta r < 0.1$), while all significance levels remained robust. As such, common method bias does not seem to be an issue in our data.

Measures

All items in our survey were measured using seven-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree). Along with the new technological frame scale, we included 12 items adapted from Dunham et al. (1989) to measure attitudes towards change, and four items from Meyer and Allen (1997) to measure affective commitment.

To ensure that our measure of technological frames explains variance over and above alternative theoretical explanations, we controlled for variables that could affect actors' attitudes towards technology-induced change and affective commitment (Elias, 2009; Meyer and Allen, 1997). As job satisfaction is associated with corporate actors' attitudes towards change (Oreg et al., 2011), we controlled for this aspect using the scale developed by Agho et al. (1992). Furthermore, perceived job insecurity causes additional uncertainty when interpreting and assessing technological frames. Thus, we measured this control in line with Ashford et al. (1989). As research often operationalizes technological frames using proxies that assess actors' individual experiences (Eggers and Kaplan, 2013; Furr et al., 2012), we also controlled for current job position (employed/self-employed), years of experience in the current position, age, gender, family status, and highest education level (high school/vocational training/university).

Results

Measurement assessment. We used the same approach to measurement assessment (and the same criteria) as for the CFA (see Tables X and XI). The standardized factor loadings in the model ranged from 0.71 to 0.91. Consequently, we assumed good IR. The CR values were high at 0.89 to 0.96. As the AVE values were all significantly higher than 0.5 (ranging from 0.63 to 0.80) and as the squared AVE values exceeded the inter-construct correlations, convergent and discriminant validity were established. The HTMT criterion again supported the latter, as all of the HTMT criteria were less than 0.85 and their 95 per cent confidence intervals did not include one.

Structural model results. We tested this simple structural model using a two-step procedure (Table XII). The first model included only the control variables, while the technological frame construct was added to the second model. The control variables explain 22 per cent of the variance in attitudes towards change and 59 per cent of the variance in affective commitment. The second model replicated the previously uncovered effects between technological frames and attitudes towards change ($\beta = 0.547$; $p < 0.001$), and between technological frames and affective commitment ($\beta = 0.122$; $p < 0.001$). The full model explained 48 per cent of the variance in attitudes towards change and 60 per cent of the variance in affective commitment. While the size of technological frames' effect on attitudes towards change is substantial ($f^2 = 0.49$), their effect on affective commitment is relatively small ($f^2 = 0.04$). The Stone-Geisser's Q^2 values (omission distance = 7) for both endogenous constructs are significantly above zero, indicating that the model has predictive relevance for these two constructs. As these findings are in line with previous research, they support the measurement scale's nomological validity.

Table X. Descriptive statistics and inter-correlations

	Mean	*Standard Deviation*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*
1 Application value	4.853	1.387	1																	
2 Industry influence	4.581	1.438	0.582	1																
3 Organizat-ional influence	4.041	1.568	0.57	0.707	1															
4 Personal attitude	5.151	1.239	0.701	0.46	0.412	1														
5 Supervisor influence	4.222	1.5	0.542	0.627	0.727	0.461	1													
6 Attitude towards change	4.968	1.040	0.534	0.435	0.425	0.585	0.486	1												
7 Affective commitment	4.94	1.343	0.254	0.192	0.152	0.252	0.297	0.482	1											
8 Job satisfaction	5.03	1.25	0.203	0.124	0.117	0.219	0.239	0.433	0.748	1										
9 Perceived job insecurity	2.225	1.23	0.029	0.073	0.125	0.015	0.046	0.111	−0.204	0.225	1									
10 Job status: self-employed	0.058	0.233	−0.042	0.008	0.022	0.023	0.026	0.08	0.015	0.032	0.012	1								
11 Job status: employed	0.524	0.499	−0.053	0.009	0.074	0.079	0.115	0.024	0.064	−0.051	0.025	0.259	1							
12 Age	45.618	13.029	0.064	0.038	0.047	0.06	0.008	0.039	0.231	0.183	0.073	0.092	0.076	1						
13 Years of experience in current role	13.323	2.153	0	0.021	0.006	0.012	0.014	0.034	−0.198	0.146	0.091	0.027	0.02	0.154	1					
14 Highest education: school	0.347	0.477	0.03	0.047	0.02	0.022	0.007	0.009	0.028	0.003	0.001	0.023	0.006	0.079	0.148	1				
15 Highest education: vocational training	0.178	0.383	−0.164	0.147	0.113	0.117	0.123	0.077	0.003	0.002	0.052	0.069	0.019	0.069	0.121	0.684	1			
16 Highest education: university	0.468	0.499	0.201	0.149	0.137	0.149	0.18	0.126	0.046	0.005	0.055	0.076	0.04	0.02	0.034	0.339	0.436	1		
17 Gender: female	0.339	0.473	0.17	0.162	0.147	0.03	0.098	0.04	0.05	0.072	0.052	0.05	0.004	0.095	0.055	0.09	0.109	0.043	11	-
18 Family status: married	0.497	0.5	0.117	0.101	0.084	0.045	0.086	0.094	0.225	0.173	0.019	0.024	0.022	0.227	−0.418	0.095	0.019	0.103	0.018	1

Table XI. Test for nomological validity – assessment of the additional reflective constructs

Construct	*Item*	*Mean*	*Std. Dev*	*Std. Factor Loading*	*t-value*
Attitude towards change *α = 0.95* *CR = 0.94* *AVE = 0.64*	I usually support new ideas	5.33	1.24	0.72	26.98
	I find most changes pleasing	4.83	1.18	0.81	49.51
	I usually benefit from change	4.79	1.28	0.81	45.90
	I intend to do whatever possible to support change	4.85	1.29	0.84	55.47
	Change usually benefits the organization	5.19	1.25	0.80	39.18
	Change usually helps improve unsatisfactory situations at work	5.12	1.32	0.79	43.17
	Most of my coworkers benefit from change	4.76	1.32	0.77	35.60
	I am inclined to try new ideas	5.49	1.27	0.78	38.16
	I look forward to changes at work	5.10	1.29	0.82	49.01
	I often suggest new approaches to things	4.69	1.44	0.73	32.54
	Change often helps me perform better	4.70	1.37	0.82	51.41
	Changes tend to stimulate me	4.80	1.37	0.84	56.73
	Other people think that I support change	4.95	1.34	0.83	56.10
Affective commitment *α = 0.84* *CR = 0.89* *AVE = 0.68*	Working for this company has high personal value for me	5.10	1.58	0.89	84.88
	I would be very happy to spend the rest of my career with this organization	5.39	1.61	0.82	43.42
	I feel as if this organization's problems are my own	4.88	1.68	0.85	48.34
	I enjoy discussing my organization with people outside of it	4.38	1.68	0.71	24.85
Perceived job insecurity *α = 0.88* *CR = 0.94* *AVE =0.63*	I believe the future of my current job is uncertain	2.65	1.68	0.72	17.49
	It is very likely that…				
	… I may be fired	2.29	1.60	0.81	30.15
	… I may be pressured to accept early retirement	2.00	1.49	0.74	16.43
	… I may be laid off for a short while	2.41	1.69	0.81	30.81
	… I may be laid off permanently	1.98	1.43	0.84	32.51
	… I may lose my job and be moved to a lower level job in the organization	2.02	1.41	0.830	28.51
Job satisfaction *α = 0.90* *CR = 0.93* *AVE =0.71*	I feel fairly satisfied with my job	5.31	1.39	0.88	77.70
	I find real enjoyment in my job	5.35	1.40	0.91	100.73
	I like my job better than the average person	4.98	1.49	0.86	64.22
	I would not consider taking another kind of job	4.68	1.76	0.75	29.14
	Most days I am enthusiastic about my job	4.84	1.41	0.80	36.03

Note: The measurement assessment of the technological frames construct revealed no significant differences from Table 7. It is, therefore, not reported.

Table XII. Test of nomological validity – structural model results

	Dependent Variables			
	Attitude Towards Change		*Affective Commitment*	
	Only controls	*Full Model*	*Only controls*	*Full Model*
Independent Variables				
Technological frame		0.547*** (0.038)		0.122*** (0.030)
Controls				
Job satisfaction	0.445*** (0.043)	0.303*** (0.039)	0.709*** (0.026)	0.678*** (0.028)
Perceived job insecurity	−0.023 (0.044)	−0.084* (0.036)	−0.032 (0.027)	−0.046 (0.027)
Job status: self-employed (0/1)	−0.081* (0.041)	−0.068* (0.034)	−0.050 (0.031)	−0.047 (0.031)
Job status: employed (0/1)	−0.018 (0.039)	0.018 (0.032)	−0.028 (0.027)	−0.020 (0.028)
Age	−0.035 (0.039)	−0.033 (0.035)	0.079** (0.027)	0.079** (0.027)
Years of experience in current role	0.039 (0.043)	0.013 (0.033)	−0.055 (0.033)	−0.061 (0.032)
Highest education: school (0/1)	0.256 (0.945)	−0.034 (0.151)	0.237 (1.002)	0.170 (0.314)
Highest education: vocational training (0/1)	0.249 (1.007)	−0.009 (0.158)	0.249 (1.072)	0.188 (0.329)
Highest education: university (0/1)	0.309 (0.811)	0.002 (0.124)	0.218 (0.863)	0.148 (0.252)
Gender: female (0/1)	0.051 (0.038)	−0.022 (0.032)	0.004 (0.030)	−0.013 (0.030)
Family status: married (0/1)	0.029 (0.041)	−0.008 (0.035)	0.057 (0.031)	0.049 (0.031)
R^2	0.22	0.48	0.59	0.60
f^2 (technological frame)		0.49		0.04
Q^2	0.14	0.30	0.39	0.39

Notes: * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$, Values in parentheses show standard errors.

DISCUSSION AND CONCLUSION

The expanding research into technological frames seeks to understand collective outcomes, such as technology's use patterns within a corporation (Anthony, 2018; Mazmanian, 2013; Orlikowski and Gash, 1994), technology implementation (Davidson, 2006; Young et al., 2016), and technology trajectories (Hoppmann et al., 2020; Kaplan and Tripsas, 2008; Seidel et al., 2020). However, insights into the individual conditions of technological frames that can explain heterogeneity in their consequences are lacking. We argue that this is partly due to a failure to focus on the microfoundation of the theory on technological frames and the absence of a measurement instrument for directly assessing the construct. To address these research gaps, this study provides the theoretical underpinnings and a measurement instrument that can explain and assess variety in technological frames on an individual level.

In this paper, we advance our understanding of the microfoundations of technological frames by synthesizing previously disconnected insights within a multidimensional conceptualization on the individual level. In line with extant research, we reveal that technological frames are shaped by different antecedents: (1) personal attitude, (2) application value, (3) organizational influence, (4) leader influence, and (5) industry influence. Nevertheless, literature tend to investigate these insights separately. For instance, scholars either focus the experience of corporate actors (Orlikowski and Gash, 1994; Schmitz and Fulk, 1991; Young et al., 2016) or their affiliations within the industry as an antecedent of technological frame (Allen and Kim, 2005; Van Burg et al., 2014; Kaplan and Tripsas, 2008). By integrating these disconnected insights, we show that the technological frame of a corporate actor is a complex synthesis of varying dimensions. In turn, these dimensions are the antecedents of technological frames and shape the interpretation of digital technologies.

We support this theorizing by developing novel methodological means that unpack the reasons for the heterogeneity in the collective consequences of technological frames. In particular, the multi-step scale-development procedure supported the multidimensional structure of the construct as it resulted in a higher-order measurement instrument encompassing five dimensions. Our findings support the idea that actors' technological frames affect their reactions to organizational changes induced by the implementation of digital technologies (Davidson, 2006; Herscovitch and Meyer, 2002; Young et al., 2016). In other words, different interpretations of and reactions to digital technologies can be explained by varying technological frames of corporate actors.

Implications for Theory

Our central contribution lies in theorizing and validating technological frames as a crucial cognitive mechanism through which scholars can understand how the variety of technological frames on the individual level influence their reactions to novel technologies and determine heterogeneous consequences on the collective level.

Our multidimensional conceptualization advances our understanding of the microfoundations of technological frames (Cornelissen and Werner, 2014; Felin et al., 2015; Orlikowski and Gash, 1994) by theorizing on their variety on the individual level and developing a novel measurement instrument. Although the literature provides first conceptual insights into the foundations of technological frames on the individual level (Kaplan and Tripsas, 2008), it mainly focuses on actors' social interactions to investigate how collective technological frames evolve and how they affect collective outcomes (Cornelissen and Werner, 2014; Kumaraswamy et al., 2018). In contrast to research that almost uniformly ignores the individual level as the microfoundation of collective outputs, we synthesize separate insights into one uniform and multidimensional conceptualization of an actor's technological frame. This conceptualization extends the literature by combining previously unconnected antecedents of technological frames that are rooted in the individual actors and those rooted in their affiliations with the intra- and inter-organizational social context (Bijker, 1995; Kaplan and Tripsas, 2008). Consequently, by introducing the concept of an actor's technological frame instead of primarily focusing on how social interactions shape technological frames (Cornelissen and Werner, 2014; Kaplan, 2011; Leonardi and Barley, 2010), we gain finer-grained insights into the way how individuals interpret technologies.

This refinement of extant theory takes a step toward resolving a central controversy about the consequences of technological frames on technology development, implementation, and usage (Anthony, 2018; Leonardi, 2011; Seidel et al., 2020; Young et al., 2016). Our multidimensional conceptualization can explain the variety in technological frames on the individual level (Kaplan and Tripsas, 2008; McGovern and Hicks, 2004) and thereby reconcile seemingly inconsistent and heterogeneous insights on the collective consequences of technological frames. For instance, while actors' social affiliations with the organization, leaders, and industry can result in a less attractive interpretation of a specific technology (Van Burg et al., 2014; Furr et al., 2012; Hoppmann et al., 2020), their attitudes and application values can compensate for those affiliations. An actor's technological frame can result in a positive interpretation of the technology, even if that actor's colleagues and corporate leaders interpret the technology as less positive. Since our multidimensional conceptualization of technological frames takes different antecedents into account, our theorizing can explain why some actors develop a homogenous use pattern and others develop a negative attitude towards change that can fuel resistance (Anthony, 2018; Azad and Faraj, 2008; Leonardi, 2011; Young et al., 2016). Thereby, our refinement of the literature offers researchers the theoretical means to understand how the variety of technological frames on the individual level are interrelated to the heterogeneous consequences of technological frames on the collective level.

In addition, our theorizing enables us to develop a novel measurement instrument that offers researchers the opportunity to theorize and test models of technological frames. Thereby, we provide the methodological means to extend established qualitative measurements (see Cornelissen and Werner, 2014) as well as the few available quantitative measurements (Fulk, 1993; Schmitz and Fulk, 1991). Research typically relies on thematic content analysis, qualitative methodologies, and indirect proxies of an actor's biographical background (Cornelissen and Werner, 2014; Kaplan, 2011; Leonardi and Barley, 2010). We complement these approaches by offering a way of directly assessing an actor's technological frame. Consequently, this study provides a basis for combining different data sources in quantitative empirical research and for developing sophisticated experimental designs. For instance, instead of relying on archival data, such as letters to shareholders (Cornelissen and Werner, 2014; Kaplan, 2011), researchers can directly apply our scale to assess technological frames and investigate corporate strategizing before an interpretation becomes explicitly codified as part of official corporate documents. Notably, our scale can be applied in combination with archival data sources (e.g., letters to shareholders, patent data, and reports). The combination of diverse data sources at different points in time enables researchers to unpack variations in collective technology use patterns based on their constitutive components.

Implications for Practice

Our results are also useful for practitioners who develop and execute strategies for coping with digital technologies. Corporations can apply the scale presented here to analyse how corporate actors interpret new digital technologies in general and to determine whether they are likely to support their implementation. When faced with a choice of different digital technologies for possible implementation, practitioners can use the scale to select the technology that the highest number of strategic actors find attractive.

Technological frames can also be instrumental when managing technological change. In such situations, corporations can rely on the scale to assess actors' interpretations of such change. Corporations can also apply our research to understand the dysfunctionalities that arise when corporate actors resist attempts to implement new technologies or develop heterogeneous patterns of use.

As our measurement scale enables comparisons of different interventions' effects and of effects over time, practitioners can apply it to tailor technology-induced organizational change so that it is consistent with stakeholders' needs and requirements. Moreover, practitioners can design interventions, such as professional training, to enhance a technology's attractiveness or effectively adapt its various properties.

Limitations, Boundary Conditions, and Future Research

Despite our comprehensive theorizing and rigorous scale-development process, this research is not without its limitations. However, future studies may improve on and extend the results of this research. In particular, we provide the theoretical and methodological means for rigorous modelling and testing of the consequences of technological frames, and for additional multi-level research. In response to identified research gaps on the microfoundation of technological frames and the limitations of this study, we highlight three promising research areas – *social interaction*, *heterogeneous consequences*, and *managing technological frames* (see Table XIII). Each of these research areas build on existing conversations in the literature on corporate strategy and technological frames, where they can create new discussions and insights that improve our understanding of how corporations shape opportunities and cope with the challenges of the digital age.

First, this study opens up avenues for researchers to explore the *social interactions* within and beyond corporate boundaries. Within corporate boundaries, researchers can utilize this study's results to investigate how similarities and differences among technological frames affect their collective aggregation and emergence (see Felin et al., 2015). Future research can extend qualitative insights into specific behaviours, such as framing, political behaviour, and resistance (Hoppmann et al., 2020; Roeth et al., 2019; Young et al., 2016), and explore how these behaviours shape the development of collective technological frames (Azad and Faraj, 2008). Future research can also incorporate insights into the characteristics of technological frames, such as their content, structure, and salience in order to understand the interrelation between the organizational and industrial context and technological frames (Hoppmann et al., 2020; Kaplan and Tripsas, 2008). In particular, research in different organizational contexts and industries can extend the boundaries of this study. While we sampled actors in the craft and construction industry that are less likely to be experienced with digital technologies, actors in knowledge-intensive

Table XIII. Future research on technological frames and corporate strategizing in the digital age

Research Areas	*Research Questions*
Social interaction	**Within Corporate Boundaries** • How do the similarities and differences among technological frames affect their collective aggregation and emergence? • What specific behaviours (e.g., framing, political behavior, and resistance), characteristics of technological frames (e.g., content, structure, and salience), and organizational contexts shape this relationship? • How does the corporation's history with other (digital) technologies affect social interactions at multiple levels that shape technological frames? • How do digital tools affect the social interactions that shape collective technological frames?
	Beyond Corporate Boundaries • How does the variety of technological frames among actors in a broader ecosystem (e.g., users, partners, competitors, complementors, and institutions) affect collective technological frames? • How do blurring market and industry boundaries, new ventures, and the rise of new industries in the digital age influence the technological frame(s) of corporations? • How do the technological frames of corporate actors shape interfaces with external actors (e.g., information exchange, collaboration, and competition) and vice versa? • How do virtual interactions between corporate and external actors on digital platforms and other digital tools shape collective technological frames?
Heterogeneous consequences	**Contingencies** • How do the characteristics of digital technologies (e.g., materiality, scale, scope, and life cycle) shape heterogeneity in the consequences of technological frames? • What internal contingencies (e.g., power, legitimacy, decision-making procedures, and culture) can explain heterogeneity in the consequences of technological frames for new product development, technology implementation, technology use patterns, and technology trajectories? • How do external contingencies (e.g., environmental turbulence, new competitors, and market characteristics) influence the consequences of technological frames?
	(In-)Congruence and (In-)Consistence of Technological Frames • When can incongruent and inconsistent technological frames within and between corporate actors/groups be functional? For instance, can they stimulate creativity in new product development, knowledge generation and learning, renewal of corporate capabilities, or the development and exploitation of resources? • How can congruent or consistent technological frames be dysfunctional (e.g., path dependencies, rigidities, inertia) and, thereby, challenge the digital transformation? • Under what internal and external conditions can incongruent or inconsistent technological frames among corporate actors/groups support digital transformation?
Managing Technological Frames	**Leadership** • How can corporate leaders manage the development of specific technological frames that facilitate digital strategizing, the implementation of digital technologies, the development of digital innovation, and the corporation's digital transformation? • How can corporate leaders negotiate, communicate, and legitimize a particular technological frame in order to enhance its salience to others? • How do different and novel roles, status differences, expertise, and capabilities within the top management team influence the development of (collective) technological frames?

Table XIII. *Continued*

Research Areas	*Research Questions*
	Developing Strategies • How can technological frames foster the identification of opportunities and threats in the digital age? • How do technological frames enable or inhibit the CEO's and the top management team's attention to, discovery of, or creation of opportunities for digital transformation? • How do technological frames shape the use of new digital tools in strategic planning and strategic decision-making?
	Executing Strategies • How do technological frames influence the development, configuration, and reconfiguration of corporate resources, capabilities, and business models to engage in and cope with digital transformation? • How can corporations steer the development of technological frames that support the execution of strategies? • What are the consequences of steering instruments (e.g., interventions, incentives, training) for the execution of strategies? • What tools, methods, and collaborative approaches can be used to manage and control the development of suitable technological frames during strategy execution?

industries tend to be accustomed to these technologies (Anthony, 2018; Bailey et al., 2010). Although our measurement assesses actors' prior experience, future research that samples different industries and cultural settings could help determine the generalizability of our results.

As conceptual and qualitative research has started to examine how collective technological frames are shaped beyond corporate boundaries (Kaplan and Tripsas, 2008; Kumaraswamy et al., 2018; Van Burg et al., 2014), researchers can enhance our knowledge by investigating how variety among actors within a broader ecosystem affects the development of a collective technological frame. While conceptual research offers rich theoretical insights into potential incongruencies in manifold technological frames during an era of disruption (Kaplan and Tripsas, 2008; Kumaraswamy et al., 2018), future research could investigate how digitalization changes market and industry boundaries, creates new ventures, and gives rise to new industries that, in turn, influence technological frame(s) of cooperation, information exchange, collaboration, and competition among actors across corporate boundaries and industries (Seidel et al., 2020).

Second, this study lays the foundation for additional multi-level research that can resolve the debate regarding the *heterogeneous consequences* of technological frames by exploring the conditions able to define the consequences (Felin et al., 2015). In this study, we selected a specific digital technology to ensure that the participants had a certain new technology in mind when responding to our survey questions. A valuable extension of our research would be to test other digital and physical technologies in alternative technological life cycles (Hoppmann et al., 2020; Kaplan and Tripsas, 2008). As technological discontinuities challenge established technological frames and trigger innovation (Kaplan and Tripsas, 2008; Kumaraswamy et al., 2018), future studies can question established research advocating for the functional effects of congruent technological frames (Cornelissen and Werner, 2014; Leonardi and Barley, 2010; Young et al., 2016) by exploring their dysfunctionalities. Although we evaluated the measurement instrument's nomological validity by assessing its associations with other meaningful consequences of technological frames, we cannot empirically proof its underlying causality. Therefore, we encourage studies that investigate the consequences of technological frames by collecting longitudinal data or applying experimental research designs.

Moreover, scholars can enhance our understanding of incongruent technological frames (Azad and Faraj, 2008; Leonardi, 2011; McGovern and Hicks, 2004). As innovative outcomes in new product development are animated by conflicts, diverse competencies, and complementary capabilities (Anthony, 2018), studies can examine how incongruent technological frames can stimulate not only creativity in new product development but also knowledge generation and learning, the renewal of corporate capabilities, and the development and exploitation of resources.

Third, given the substantial strategic consequences of technological frames for corporations' reactions to technological change as well as their new product development, technology implementation, and technology trajectories, additional research can enhance our understanding of how corporations can *manage technological frames*. As corporate leaders' technological frame(s) shape(s) reactions to technological change and technology implementation (Furr et al., 2012; McGovern and Hicks, 2004), studies can explore how leaders shape technological frames in order to purposefully manage their consequences. Such research could investigate potential intertemporal influences of the hierarchical dimensions of our technological frame construct. As the antecedents of technological frames are theoretically interrelated, we developed a hierarchical measurement instrument. However, industry effects may also determine collective corporate frames that, in turn, influence the selection of a corporate leader (Furr et al., 2012; Kaplan and Tripsas, 2008). Further research can also investigate how technological frames can shape the development and execution of digital strategies since technological frames affect the implementation of digital technologies as well as related usage patterns, and human information processing (Anthony, 2018; Cornelissen and Werner, 2014; Hanelt et al., 2021; Leonardi and Barley, 2010).

CONCLUSION

When digital technologies confront corporate actors with substantial degrees of uncertainty and complexity, they rely on their technological frames to interpret, assess, and shape a technology's development, usage, and trajectory. Researchers have not, however, sought to uncover the potential reasons for the heterogeneity in the collective consequences of technological frames by exploring the varying antecedents of technological frames on the individual level. Our research emphasizes this shift in that direction and, thus, contributes to the microfoundation of technological frames. In particular, we synthesize separated insights into multidimensional conceptualization of an actor's technological frame and develop a corresponding measurement instrument. We believe that these novel theoretical and methodological means represent a step in the direction of uncovering how the technological frames of individual actors, their interactions, and the context of those interactions shape heterogeneity in collective outcomes. This refinement of theory can also fuel further research on corporate strategy and technological frames in order to improve our knowledge on how corporations respond to and shape the challenges and opportunities of the digital age.

NOTES

[1] Although technological frames are related to similar frames of reference concepts, they are distinct in their focus on technologies (Cornelissen and Werner, 2014). For instance, Tversky and Kahneman (1981) investigate how frames function as a baseline for judgments and how they bias managerial decision-making in general. In contrast, other research applies a social construction perspective. For example, Schütz (1970) examines the related concept of a scheme of reference focusing on socially constructed typifications to understand actors' social relationships with others (Foss and Garzarelli, 2007). However, both research streams are not related to the specific context of an actor's interpretation of technologies.

[2] As reliability increased, we increased the number of raters by five for each round. Initially, we planned to use 10 raters in round 1, 15 in round 2, 20 in round 3, and 25 in round 4. However, some raters did not finish the task as promised, causing the actual number of raters to be slightly lower.

[3] We did not consider micro-firms because digitalization in this type of firm may play a fundamentally different role. Research shows that decision-making in micro-firms follows different patterns than decision-making in other firms (Liberman-Yaconi et al., 2010). Micro-firms often lack rational strategic planning and/or growth strategies. Consequently, digitalization, or even the use of digital technologies (e.g., the digital learning tool we present here) may not fall within their scope. We, therefore, decided to eliminate them to prevent potential biases.

[4] We received at least two responses for each firm. Although firm-level factors (e.g., firm culture) can influence the responses, this study draws on multiple and independent data sets. In particular, the next stage of the scale-development analyses a different sample and confirms the five dimensions of the technological frame construct. In addition to this methodological perspective, we theorize that the antecedents of a technological frame encompass multiple dimensions that also assess firm-level factors. Therefore, we can conclude that multiple responses from each firm in this data set do not threaten the validity of the results.

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