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Building skills in the context of digital transformation: How industry digital maturity drives proactive skill development

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ABSTRACT

Digital transformation is changing the employee skills that organizations need to succeed. In this context, it is increasingly important for employees to proactively develop their skills. The emerging research on employee proactive skill development has largely ignored the possible role of employees' perceptions of large-scale changes in organizations' environments in their motivation to engage in such valuable behavior. We address this gap using cognitive-affective personality system theory to explain how macrolevel development affects employee behavior. Existing data on industry digital maturity were combined with survey data of 710 higher education graduates from various organizations and industries collected at two separate time points. The results support the hypothesized positive indirect effects of industry digital maturity on proactive skill development via employees' interpretation of digitalization as controllable and as an opportunity for their organization. We discuss the implications for research and organizational practice.

1. Introduction

Digital transformation creates the need for organizations to update the skills of their workforce to remain successful (Sousa & Rocha, 2019a; van Laar, van Deursen, van Dijk, & de Haan, 2017). From a microlevel perspective, informal and proactive forms of work-related learning have gained importance (Dachner, Ellingson, Noe, & Saxton, 2021; Noe & Ellingson, 2017; Wong & Fieseler, 2018), mainly because employees need to manage their careers proactively today more than in the past (Ren & Chadee, 2017; Taber & Blankemeyer, 2015).

Proactive skill development[1] is defined as the self-initiated, future-, and change-oriented acquisition of knowledge and skills that individuals may need to master future job tasks (Claes & Ruiz-Quintanilla, 1998). This concept has recently gained attention among management scholars, who have mostly focused on investigating its individual-level predictors (e.g., Clements & Kamau, 2018; Pajic, Keszler, Kismihók, Mol, & Den Hartog, 2018; Ren & Chadee, 2017; Strauss, Griffin, & Parker, 2012; Strauss & Parker, 2018; Taber & Blankemeyer, 2015).

However, researchers have recently noted a relative dearth of empirical research on the contextual antecedents of PSD (Ren & Chadee, 2017) and have called for an integration of micro and macro perspectives in investigating the development of human capital (Noe, Clarke, & Klein, 2014). Thus, we consider this gap in the literature worthy of further empirical investigation, as macrolevel cues may influence individual perceptions and beliefs and employees' strategic, future-oriented behaviors (Helpap & Bekmeier-Feuerhahn, 2016; Maitlis & Sonenshein, 2010; Prior, Keränen, & Koskela, 2018; Strobel, Tumasjan, Spörrle, & Welpe, 2017).

We address this gap by investigating the effect of industry-level digital maturity (i.e., the extent to which particular digital technologies are used within an industry, Rammer et al., 2017) on PSD. To achieve this goal, we employ the cognitive-affective personality system[2] theory of career behavior (Heslin, Keating, & Minbashian, 2019; Mischel & Shoda, 1995) to develop and test a model that links industry digital maturity and PSD indirectly via employees' interpretations of digitalization – the change of business processes through digital technologies (cf. Verhoef et al., 2021) – as controllable and as an opportunity for and threat to their organization (Dutton & Jackson, 1987). We chose these three interpretations because previous research supports their role as cognitive categories that are used by individuals to evaluate strategically

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[1] In the following abbreviated "PSD".
[2] In the following abbreviated "CAPS".

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relevant developments in the organizational environment (Jackson & Dutton, 1988; Saebi, Lien, & Foss, 2017; Sharma, 2000; Thomas, Clark, & Gioia, 1993). Additionally, to account for potential person-situation interaction effects as conceptualized in CAPS theory (Heslin et al., 2019; Mischel & Shoda, 1995), we include proactive personality in our model due to its well-documented role in predicting proactive behaviors (Fuller & Marler, 2009; Tornau & Frese, 2013; Wu, Parker, Wu, & Lee, 2018).

First, we contribute to understanding and fostering employee self-initiated skill development in organizations (e.g., Bednall & Sanders, 2017; Dachner et al., 2021; Pajic et al., 2018; Ren & Chadee, 2017; Sousa & Rocha, 2019b; Strauss & Parker, 2018; Taber & Blankemeyer, 2015). While extant research has concentrated on personality and motivation as drivers of PSD, we focus on the role of employee perceptions of their organization's strategic environment for PSD. This phenomenon is relevant for understanding how ongoing macrolevel changes affect employee engagement in self-initiated learning (e.g., Claes & Ruiz-Quintanilla, 1998; Ren & Chadee, 2017; Taber & Blankemeyer, 2015), a behavior that can support organizational success in digital transformation (Wong & Fieseler, 2018).

Second, we contribute to the micro-organizational behavior literature concerning how macrolevel factors translate into microbehavior (Johns, 2018; Molina-Azorín, Pereira-Moliner, López-Gamero, Pertusa-Ortega, & Tarí, 2020) by examining how technology-driven forces in the broader organizational environment, namely, digitalization, affect employee perceptions and subsequent behaviors. Previous research in this field has focused mostly on intraorganizational factors as predictors of group- or employee-level outcomes or on the links between the broader organizational environment and the perceptions and subsequent behaviors of managers (Johns, 2018; Molina-Azorín et al., 2020). In contrast, we examine top-down processes from the organizational environment via employee perceptions to employee behavior. As such, we address Johns' (2018) recommendations to explore the mediators of more distal, omnibus contextual cues in the prediction of microlevel behavior. Moreover, examining digitalization as a situational stimulus of individual perceptions contributes to this field because this relation has rarely been examined.

Third, we contribute to emerging research on organizational behavior that focuses on the consequences of digital transformation for organizations and their members (Cascio & Montealegre, 2016; Sousa & Rocha, 2019a; van Laar et al., 2017; Wong & Fieseler, 2018). We enhance knowledge in this field by applying a theoretical framework, namely, CAPS theory (Heslin et al., 2019; Mischel & Shoda, 1995), that has rarely been investigated in this literature and examining how digitalization affects employees' cognition and behavior.

2. Theory and hypothesis development

2.1. Proactive skill development

PSD describes individuals' self-initiated, future-, and change-oriented development of their competencies with the aim of mastering the tasks of their occupation and actively creating their own career (Claes & Ruiz-Quintanilla, 1998). PSD is one of four proactive career behaviors, in addition to proactive career planning, proactive consultation behavior, and proactive networking behavior (Claes & Ruiz-Quintanilla, 1998), and is a part of career initiative behavior (Seibert, Kraimer, & Crant, 2001).

A few recent studies have examined the antecedents of PSD, including conscientiousness and career adaptability (Pajic et al., 2018), career goal commitment and a mastery approach (Clements & Kamau, 2018), training interventions and individuals' future focus (Strauss & Parker, 2018), career networking behavior and work pressure (Ren & Chadee, 2017), future work self and confidence (Taber & Blankemeyer, 2015), experiences of hierarchical mobility, employment and unemployment, job type (blue and white collar), and characteristics of national cultures (Claes & Ruiz-Quintanilla, 1998). Enhancing these findings, in the following section, we present our research model of how macrolevel cues might influence employees' PSD, building on CAPS theory (Heslin et al., 2019; Mischel & Shoda, 1995).

2.2. Cognitive-Affective personality system theory as a framework for understanding proactive skill development in the context of digital transformation

CAPS theory (Mischel, 1973; Mischel & Shoda, 1995; Shoda, Mischel & Wright, 1994) explains how individual behavior results from both individuals' personality system and situational factors. CAPS theory has recently been applied to various behavioral outcomes in management and organizational behavior research (e.g., job performance, Frieder, Wang, & Oh, 2018; leadership, Gottfredson & Reina, in press; and withdrawal behaviors, Zimmerman, Swider, Woo, & Allen, 2016). By applying CAPS theory to career behaviors, Heslin and coauthors (2019) recently developed a model in which situational cues and personality traits jointly activate cognitive and affective patterns (i.e., cognitive-affective units[3]), which, in turn, evoke career-enabling behaviors, such as skill development. Thus, CAPS theory suggests that the CAUs (e.g., interpretations of situations) activated in the perceivers of situations rather than the situations per se determine behavior, implying that situational cues have indirect effects (e.g., Heslin et al., 2019; Mischel & Shoda, 1995; Shoda & Mischel, 2006). In line with this general CAPS model, in our research model (Fig. 1), we propose that industry digital maturity functions as a situational cue that activates individual interpretations (CAUs) regarding digitalization (mediators), which, in turn, affect PSD.

Industry digital maturity reflects the degree to which organizations within an industry have acted to profit from digitalization by implementing novel processes, tools, or methods related to this technology-driven development (Rammer et al., 2017). We argue that at higher levels of industry digital maturity, employees' CAUs relating to digitalization become more strongly activated, as they perceive what their own and other organizations in the industry do in response to digitalization (e.g., through internal and public media). Specifically, we propose that industry digital maturity enhances the degree to which employees perceive *controllability* (i.e., effective actions can be taken to resolve an issue, Dutton, Walton, & Abrahamson, 1989), *opportunity* (i.e., there is sufficient qualification, and gains and positive outcomes can be expected, Jackson & Dutton, 1988), and *threat* (i.e., there is too little qualification, and negative outcomes or potential losses can be expected, Jackson & Dutton, 1988) regarding digitalization.

Additionally, CAPS theory and research suggest interactive effects between situational cues and personality traits on CAUs and, subsequently, behavior (Heslin et al., 2019; Mischel & Shoda, 1995). Therefore, we investigate whether proactive personality (Bateman & Crant, 1993) moderates the link between industry digital maturity and individual cognition (Fig. 1).

In the following sections, consistent with CAPS theory (Heslin et al., 2019; Mischel & Shoda, 1995), we derive our hypotheses concerning the links among situational cues, individuals' interpretations of such cues, and subsequent behavior. Our study focuses on the cognitive "encodings" and "expectancies and beliefs" types of CAUs because CAPS theory suggests that cognition-related CAUs are activated first, i.e., most directly in response to situational cues. However, other types of CAUs, which are not the focus of our study (namely, "affect", "goals and values" and "competencies and self-regulatory plans"), may be subsequently involved in generating PSD (cf. Heslin et al., 2019; Mischel & Shoda, 1995, 2010; Shoda & Mischel, 2006).

[3] In the following abbreviated "CAUs".

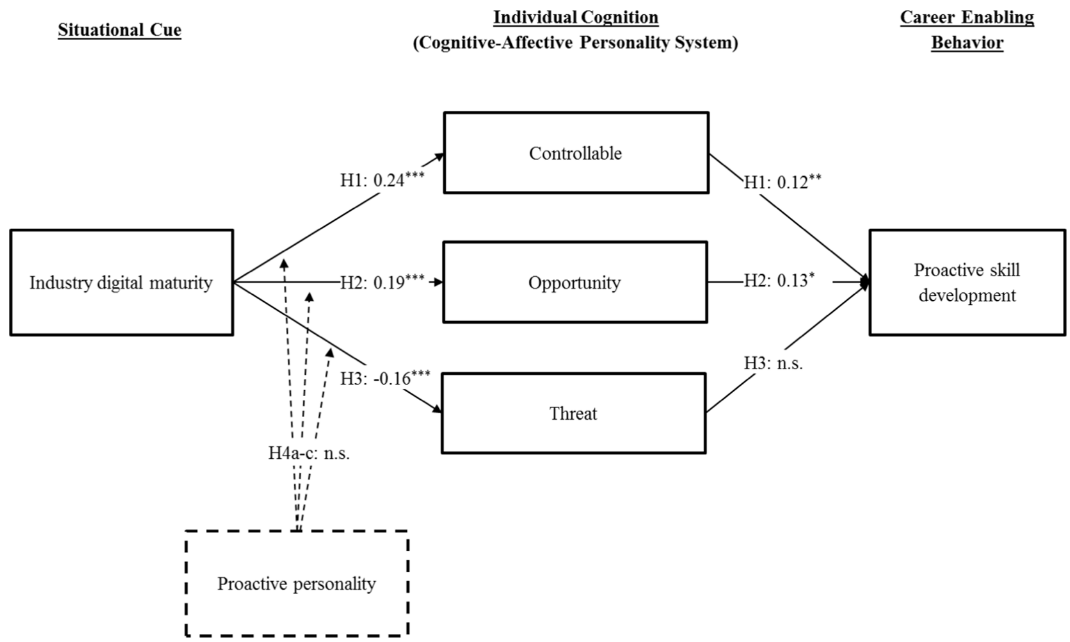

Fig. 1. Research model of proactive skill development in response to industry digital maturity and employees' interpretations of the consequences of digitalization for their organization.
Note. Beta coefficients obtained from 5,000 bootstrapped samples reported; N = 710. n.s. = not significant. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

2.3. Positive indirect effect of industry digital maturity on PSD via interpreting digitalization as controllable

In terms of CAPS theory, perceived controllability can be conceptualized as an "expectancies and beliefs" type of CAU (Fig. 1). This type of CAU reflects individual mastery experiences and self-efficacy in attaining goals (Heslin et al., 2019; Mischel & Shoda, 1995), such as in the case of perceived control (Bandura & Wood, 1989) and the use of "controllable" as a cognitive label for a situation (Dutton et al., 1989).

We argue that at higher levels of industry digital maturity, information regarding digital tools, products, and processes is more readily available to employees (cf. Rammer et al., 2017), for instance, through media, fairs, and conferences. Moreover, many types of digital tools implemented by organizations facilitate access to and management of information (cf. Rammer et al., 2017). This facilitated access to information, including information concerning how to manage digitalization, should support interpretations of digitalization as controllable in their organization (cf. Kuvaas, 2002; Thomas et al., 1993). Although it could also be argued that employees may perceive less control in situations of change, previous research has shown that a perceived lack of control and uncertainty tend to be associated with limited progress, lack of information, and low predictability (e.g., Neumann, 2017; Harvey & Victoravich, 2009; Kiefer, 2005). Therefore, we assume that a positive relationship exists between industry digital maturity and individual interpretations of digitalization as controllable.

We further suggest that employees' interpretations of digitalization as controllable are positively related to PSD because theoretically, perceived control maps onto the "can do" proactive motivational state that facilitates proactive behaviors (Parker, Bindl, & Strauss, 2010). Similarly, previous research has shown that work-related concepts that involve similar perceptions of control, such as job autonomy, job control, and control appraisal, support proactive behaviors (e.g., proactive work behavior, Sonnentag & Spychala, 2012; personal initiative, Frese, Kring, Soose, & Zempel, 1996; Frese & Fay, 2001; Ohly, Sonnentag, & Pluntke, 2006; Ohly & Fritz, 2010; Speier & Frese, 1997; and learning-related outcomes, Parker & Sprigg, 1999). In this vein, earlier research suggests that a lack of job control inhibits proactive work behavior (Parker et al., 2010).

In summary, therefore, we propose the following hypothesis:

H1. Industry digital maturity has a positive indirect effect on employee PSD through employees' interpretations of digitalization as controllable for their organization.

2.4. Positive indirect effect of industry digital maturity on PSD via interpreting digitalization as an opportunity

Consistent with Heslin and coauthors (2019), Mischel and Shoda (1995, 2010) and Zimmerman and colleagues (2016), we propose that individual interpretations of industry digital maturity as an opportunity and/or as a threat are "encoding" types of CAU (Fig. 1). This type of CAU describes individuals' mental representations of objective situations that include categorizations and evaluations of situational characteristics (Mischel & Shoda, 1995, 2010).

Individuals should interpret digitalization as an opportunity when they expect gains and positive outcomes (cf. Jackson & Dutton, 1988). We argue that employees who work in industries with a high level of digital maturity perceive that digitalization provides possible gains and opportunities for an organization that can be realized. For instance, practitioners (e.g., Bessen & Frick, 2018; Rosemann, Kowalkiewicz, & Dootson, 2017) and scholars (e.g., Iansiti & Lakhani, 2014; Kiel, Müller, Arnold, & Voigt, 2017; Kohli & Melville, 2019; World Economic Forum, 2018) suggest that organizations that adapt their business models or ways of value creation in view of digital opportunities may be very successful, at least under some conditions (Eggers & Park, 2018). Such observations arguably instill in employees perceptions of potential gains and opportunities from digitalization for the organization and, in turn, for individual job tasks and careers.

For instance, regarding digitalization, such opportunities may be facilitated through selling products and interacting with stakeholders or job opportunities in the emerging areas of electronic monitoring, robotics, big data analysis, and digital collaboration (Cascio & Montealegre, 2016; Colbert, Yee, & George, 2016). We argue that such perceptions of opportunities from digitalization drive a motivational state that supports proactive behaviors, such as PSD, namely, the "reason to" proactive motivational state (Parker et al., 2010). Specifically, we propose that interpreting digitalization as an opportunity for an organization gives employees a "reason to" develop their skills to enable them to benefit from their perceived opportunities for digitalization.

Therefore, we hypothesize:

H2. Industry digital maturity has a positive indirect effect on employee PSD through employees' interpretations of digitalization as an opportunity for their organization.

2.5. Positive indirect effect of industry digital maturity on PSD via interpreting digitalization as a threat

As individuals may interpret equivocal phenomena as both an opportunity for and a threat to organizations (Anderson & Nichols, 2007; Gilbert, 2006; Jackson & Dutton, 1988; Plambeck & Weber, 2010), we also propose that employees' interpretation of digitalization as a threat is a mediator in the link between industry digital maturity and PSD. Individuals should interpret digitalization as a threat if they perceive this macrolevel cue as negative, expect (personal) losses from reacting to it, and perceive its characteristics as ambiguous or threat-distinctive rather than neutral (Jackson & Dutton, 1988). Previous research shows that individuals tend to trust and value new technologies if these technologies are endorsed and legitimized by others, especially experts (Elsbach & Stigliani, 2019). At higher levels of industry digital maturity, employees should observe that employees in comparable organizations, i.e., "legitimate others" (cf. Elsbach & Stigliani, 2019), tend to use digital tools (cf. Rammer et al., 2017). This information should decrease the likelihood that employees perceive digitalization as ambiguous and risky (Elsbach & Stigliani, 2019) or threatening (Jackson & Dutton, 1988). Therefore, we assume that a negative link exists between industry digital maturity and individual interpretations of digitalization as a threat.

Regarding the link between interpretations of digitalization as a threat to an organization and PSD, previous research finds that proactive career behaviors (specifically career planning) may be inhibited through perceived job insecurity (i.e., fear of the future and perceived powerlessness due to the perception that one's current employment is unstable; Klehe, Zicic, Van Vianen & De Peter, 2011). Similarly, qualitative data indicate that contextual factors associated with downsizing conditions, fear of negative consequences, and uncertainty may decrease the likelihood that middle managers are willing to behave proactively (Dutton, Ashford, O'Neill, Hayes, & Wierba, 1997). Similarly, career adaptability (i.e., individuals' resources and readiness to cope with career-related changes) should be inhibited in threatening situations (Johnston, 2016). Hence, we propose that perceptions of threat have a negative effect on PSD.

In summary, these two negative links among industry digital maturity, employees' interpretations of threat, and PSD should result in the following overall positive indirect effect:

H3. Industry digital maturity has a positive indirect effect on employee PSD through employees' interpretations of digitalization as a threat to their organization.

2.6. Proactive personality as a moderator of indirect links between industry digital maturity and PSD

CAPS theory proposes that person-situation interactions occur under the conditions that situational cues are relevant to a personality trait and that cues are weak enough to permit trait-dependent individual differences in behavior (Heslin et al., 2019; Mischel & Shoda, 1995, 2010; consistent with trait activation theory, Tett & Guterman, 2000). We argue that industry digital maturity is a situational cue that allows the proactive personality to become salient (cf. Heslin et al., 2019; Tett & Guterman, 2000), as digital transformation is associated with considerable uncertainty regarding the behavioral consequences of and best practices in response to this development (Cascio & Montaelegre, 2016; Colbert et al., 2016). Furthermore, we argue that industry digital maturity and proactive personality have common characteristics, namely, the need or inner drive for future- and change-oriented action, which evoke an interaction between these two factors (regarding proactive personality see, e.g., Bateman & Crant, 1993; regarding industry digital maturity see, e.g., Rammer et al., 2017).

Regarding the interpretations of more proactive employees, previous research suggests that more proactive individuals are more likely to think that they themselves and other (proactive) organizational members can influence and control macrolevel developments (cf. Ashford & Black, 1996; Bateman & Crant, 1993; Feldman, 1981; Parker & Sprigg, 1999; Ross, Greene, & House, 1977; Seibert, Crant, & Kraimer, 1999). Moreover, meta-analytic findings indicate that more proactive individuals are more likely to interpret work challenges as opportunities rather than threats (Fuller & Marler, 2009). Furthermore, considering that more proactive individuals are more likely to actively seek out opportunities in their environment (Bateman & Crant, 1993) and that individuals interpret issues in their environment selectively (Dutton & Jackson, 1987), we argue that more proactive employees are consequently less aware of threatening developments in their environment.

Consequently, having argued that the proactive personality trait is activated in the context of digitalization and influences how employees interpret the consequences of this macrolevel development for their organization, we hypothesize the following:

H4. Proactive personality moderates the strengths of the indirect relations between industry digital maturity and PSD via individual interpretations of digitalization such that the paths between industry digital maturity and individual interpretations of digitalization as (H4a) controllable, (H4b) an opportunity, and (H4c) a threat are stronger at higher levels of proactive personality.

3. Methods

3.1. Research design

To test our hypotheses, we used existing data on industry digital maturity (our independent variable) from the Mannheim Innovation Panel (Rammer et al., 2017), which was collected in 2016 (referred to as "T0" in the following). We combined these data with quantitative survey data that we collected from a cohort of employed higher education graduates at two time points (T1 and T2). Specifically, the mediating variables (interpretations as controllable, an opportunity, and a threat) and moderating variable (proactive personality) in our model were assessed at T1, and the outcome variable (proactive skill development) was assessed at T2. The first survey (T1) took place from October 2018 to January 2019, approximately 1.5 years after the participants obtained their degree. The second survey (T2) took place in September 2020, approximately 3.5 years after the participants obtained their degree.

This sample of employed graduates is particularly suitable for our study because information seeking, creating an understanding of the work environment, and learning have been suggested to be particularly relevant for organizational newcomers (Ashford & Black, 1996) and should similarly be relevant for our sample of employees with limited work experience after graduation from higher education. Moreover, previous research suggests that individual proactive behaviors vary depending on the organizational context (e.g., Crant, 2000) and occupational level (e.g., Claes & Ruiz-Quintanilla, 1998). Thus, we presumed that surveying graduates employed in different types of jobs, organizations, and industries would increase the likelihood of observing substantial variance in our participants' PSD and in our predictors of interest as needed to test our hypotheses.

The items assessed in this study at T1 were collected as a part of an annual survey of higher education graduates' university education and job entry. Following a cluster sampling strategy, this survey was offered to all the public universities in Bavaria, a German federal state, except for art colleges and the University of the Federal Armed Forces. We invited graduates from 14 (of 31) universities and universities of applied sciences that agreed to cooperate with us (specifically, all graduates, except for those who graduated in medicine, who provided a valid email or postal address for these universities). Our second survey (T2) was specifically conducted for the purpose of the present study and included almost exclusively its variables. This survey was offered to all graduates who provided a valid email address in our first survey (T1) for the purpose of contacting them with a follow-up survey. Most participants took approximately 20 minutes to complete our first questionnaire (T1) and approximately 15 minutes to complete our second questionnaire (T2). The items for this study were answered only by graduates who were employed at the time of these surveys (namely, had obtained gainful employment, traineeship, or an internship after graduation).

3.2. Sample characteristics

Of the initial 7,601 participants in the regular graduate survey (T1), 6,970 respondents (80%) fulfilled our inclusion criteria of being employed and began to respond to our additional questions. Of these, 6,922 (99%) proceeded until our last survey page. At the end of the survey, 4,213 participants left us a valid email address for a follow-up survey. Of these, 2,754 respondents started to answer our second survey, and 2,351 (85%) proceeded to the last survey page. Ultimately, 710 participants met our inclusion criteria of being regularly employed, being employed in an industry with available digital maturity information, and providing complete data regarding all our study items at both T1 and T2. Approximately thirty-five percent of our participants reported holding a bachelor's degree, while approximately fifty-four percent reported holding a master's degree or equivalent (11% did not indicate their highest educational degree). Our participants obtained degrees in different subject areas (12% humanities; 6% math and sciences; 89% engineering; 36% business, economics and law; and 6% sports, health, arts, and other[4]; classification consistent with the Federal Statistical Office Destatis, 2020). At the time of the first survey, our participants worked in a broad range of industries (21% in machine construction and the automobile industry; 14% in information technology and telecommunication services; 12% in business consultancy and marketing; 9% in technical, research and development services; and the remainder in other industries such as the electrical industry, business and financial services, manufacturing, and wholesale; classification according to Rammer et al., 2017). Our participants were, on average, 30 years old (the youngest was 24 years old, and the oldest was 56 years old), 50% of the participants identified as male, 39% of the participants identified as female (11% did not indicate their sex), and most participants had no migratory background (75% indicated that they or their parents did not migrate to Germany and that neither of their parents was born in Germany without having the German nationality).

3.3. Measures

PSD. PSD was assessed at T2 with the three items used by Strauss and Parker (2018, e.g., "Over the past weeks, to what extent have you developed skills which may be needed in the future?"; 1 = not at all to 5 = a great deal). This scale was originally established and tested by Claes and Ruiz-Quintanilla (1998) to capture respondents' self-reported PSD. Following Claes and Ruiz-Quintanilla (1998), our introductory sentence, "The following questions are about general activities in a job context", and the items' wording invited respondents to focus "on broader perspectives of the occupational track" (Claes & Ruiz-Quintanilla, 1998: 366) rather than on their adjustment to their present job, their organization, or a specific career stage. To perform robustness checks regarding potential distortions resulting from the referenced time span in this measure (e.g., seasonal effects), we included two additional variations of this measure referring to the time frames "since the beginning of 2020" (i.e., over the past eight months) and "in 2019" (i.e., over the entire past year). The Cronbach's alpha of our main measure referring to "the past weeks" was 0.90.

Interpretations of digitalization. We assessed individual interpretations of digitalization as controllable, as an opportunity, and as a threat at T1 with eight items adapted from Anderson and Nichols (2007), which were originally based on Thomas and colleagues (1993). Specifically, to assess controllability, we adapted Anderson and Nichols' (2007) two items concerning the issue of digitalization (e.g., "How do you assess the importance of digitalization for the organization in which you currently work? In my view, our organization can manage digitalization."; 1 = "I totally disagree" to 5 = "I agree completely"). Similarly, to measure individual interpretations as an opportunity and as a threat, we specified the three items with the highest factor loadings of each subscale for the issue of digitalization (e.g., for the interpretation of digitalization as an opportunity, "In my view, the future of our organization will be better because of digitalization"; for the interpretation of digitalization as a threat, "In my view, digitalization will have a negative impact on the future of our organization"). The Cronbach's alpha was 0.94 for interpretation as controllable, 0.96 for interpretation as an opportunity, and 0.95 for interpretation as a threat.

Industry digital maturity. Information on the digital maturity of the industries in which our participants worked (i.e., an index of industry digital maturity) was added to our survey data from the results of the Mannheim Innovation Panel (Rammer et al., 2017).

The results of the Mannheim Innovation Panel are the responses of nearly 11,800 companies in Germany that had more than five employees in 2016 (approximately 53% of the sample). Survey participants indicated the degree (widely, medium, poorly, not at all) to which 11 digital applications for digital networks (e.g., between service, production and logistics), internal organization and communication (e.g., web-based platforms), sales and external communication (e.g., e-commerce), and information processing (e.g., cloud applications) were used within their company at the time of the survey. Rammer and colleagues (2017) projected this information on the population of companies in Germany with more than five employees and reported the share of companies using these different digital applications, inter alia, by sector. Based on this report, we calculated industry digital maturity as the average share of companies using digital applications by sector. For each sector, we aggregated the shares of usage reported for each of the 11 digital applications and divided them by the number of applications. Because the industry classification established in the regular graduate survey did not correspond to the industry classification used in the Mannheim Innovation Panel, we had to aggregate information provided by Rammer and coauthors (2017) as described in the next paragraph. In this case, we calculated the industry-specific average shares of companies using digital applications by summing the indicated shares of usage over all 11 digital applications in each subindustry and dividing them by the product of the number of digital applications and the number of aggregated subindustries.

Specifically, industries of the two surveys were matched and, if necessary, aggregated based on the names in both surveys and the German classification of economic sectors (Federal Statistical Office Destatis, 2008) used by Rammer and colleagues (2017). For instance, to calculate the digital maturity of our mechanical engineering and vehicle construction industries, we aggregated Rammer and coauthors' (2017) information on the industries' mechanical and automotive engineering. Our final dataset contains information on 14 industries: business services; chemistry and pharmacy; electrical industry; energy, mining, and mineral oil; financial services; information technology and telecommunication; management consulting and advertising; manufacturing; media services; metal production and processing; technical and R&D services; transportation and post; water, disposal, and recycling; and wholesale. As our survey data were collected at the individual level, each participant was assigned a value of industry digital maturity based

[4] Note that the percentages do not sum up to 100% as participants were allowed to indicate more than one main subject area.

on the industry in which the participant indicated working at T1.

Proactive personality. Proactive personality was assessed with the six items used by Parker (1998; originally developed by Bateman & Crant, 1993, e.g., "I am always looking for better ways to do things"; 1 = strongly disagree to 5 = strongly agree). The Cronbach's alpha was 0.76.

4. Results

4.1. Model fit

Table 1 displays the descriptive statistics, internal consistencies, and pairwise correlations of the variables included in our study. All the analyses were conducted by applying sound diagnostic methods using SPSS Amos (IBM Corp., 2019a) and SPSS Statistics (IBM Corp., 2019b) version 26.

CFA supported our conceptualization of a five-factor model composed of PSD; individual interpretations as controllable, an opportunity, and a threat; and proactive personality. The CFA indicated a good model fit ($\chi^2[44] = 223.70$, $p < 0.000$; $\chi^2/\text{df} = 2.05$; CFI = 0.99; RMSEA = 0.04; SRMR = 0.03; Iacobucci, 2010); that is, considering these fit indices, it was better than any four- to one-factor model combining two or more of these factors. Additionally, as recommended by Fornell and Larcker (1981), the squared correlations between our latent constructs and all the other constructs were smaller than the average variances extracted for each latent construct. In summary, these results provide evidence of discriminant validity.

To address concerns of common method bias, we conducted Harman's one-factor test using exploratory factor analysis (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). An individual factor explained a maximum of 34.94% of the variance, and all our surveyed items were related to the intended factors. Furthermore, the CFA mentioned above indicated a poor fit of the one-factor model. Hence, we concluded that common method bias was unlikely to be a significant threat in this study.

To assess whether multicollinearity was a problem in this study, we calculated the VIF and the tolerances for all our regression models. The largest VIF (2.74; Model 3, Table 2) and the smallest tolerance (0.37; Model 3, Table 2) indicated no major problems of multicollinearity (Hair, Black, Babin, & Anderson, 2014).

4.2. Analyses and results

We tested our hypotheses in two sequential steps. First, we ran hierarchical regression analyses using multiple regression and bootstrapping techniques following Hayes (2017) to assess our hypothesized indirect and moderated indirect effects. We used bootstrapping because this approach does not require any assumptions on the shape of the sampling distribution, its inferences are more likely to be accurate, and its tests tend to have more power than a normal theory approach (Hayes, 2017). Specifically, following Hayes (2017), we set our bootstrapping procedures so that they drew up to 5,000 samples from our original sample of 710 units with replacement and calculated the average indirect effects as well as bootstrapped 95% confidence intervals (CIs). Second, we used Hayes' (2017) PROCESS macro to test the proposed indirect (H1, H2, H3) and moderating (H4) effects. In line with Hayes (2017), we concluded that indirect effects were significant only if their 95% CI did not include zero.

To test hypotheses 1 to 3, we ran a model in which industry digital maturity was the predictor; employees' interpretations of digitalization as controllable (H1), an opportunity (H2), and a threat (H3) were simultaneous mediators; and PSD was the outcome using model number 4 of Hayes' (2017) PROCESS macro. To test hypothesis 4, we used the PROCESS model number 7 to run a model with industry digital maturity, and the interaction between industry digital maturity and proactive personality predicted employees' interpretations as controllable (H4a), an opportunity (H4b), and a threat (H4c) while controlling for proactive personality. We standardized all the variables prior to the analyses.

Hypothesis 1 proposes that industry digital maturity has a positive indirect effect on PSD via employees' interpretation of digitalization as controllable. Supporting this hypothesis, the 95% CI [0.01, 0.06] of the indirect effect (Table 4) excluded zero and thus indicated that this indirect effect was significant. Consistently, both the effect of industry digital maturity on employee interpretation as controllable ($\beta = 0.24$, $p < 0.001$; 95% CI [0.17, 0.31]; Model 1, Table 3) and the effect of interpretation of digitalization as controllable on PSD were significant and positive ($\beta = 0.12$, $p < 0.01$; 95% CI [0.03, 0.21]; Model 2, Table 2). Hence, we concluded that hypothesis 1 was supported. The effect size of this indirect effect indicates that two employees who work in industries that differ by one standard deviation in industry digital maturity differ by approximately 0.03 standard deviations in their likelihood of proactively developing their skills as a result of this indirect relation between industry digital maturity and PSD via interpreting digitalization as controllable for an organization.

Hypothesis 2 suggests that industry digital maturity has a positive indirect effect on PSD through employees' interpretation of digitalization as an opportunity. The 95% CI [0.00[5], 0.05] of this indirect effect (Table 4) did not include zero and hence indicated that this indirect effect was significant. Specifically, our results showed a positive effect of industry digital maturity on the interpretation of digitalization as an opportunity ($\beta = 0.19$, $p < 0.001$; 95% CI [0.11, 0.26]; Model 3, Table 3) and a positive effect of the interpretation of digitalization as an opportunity on PSD, which excluded zero at the 95% CI ($\beta = 0.13$, $p = 0.05$; 95% CI [0.01, 0.25]; Model 2, Table 2). Therefore, we concluded that hypothesis 2 was supported. The effect size of this indirect effect indicates that two employees who work in industries that differ by one standard deviation in industry digital maturity differ by approximately 0.02 standard deviations in their likelihood of proactively developing their skills as a result of this indirect link between industry digital maturity and PSD via interpreting digitalization as an opportunity for their organization.

Hypothesis 3 proposes that industry digital maturity has a positive indirect effect on PSD via employees' interpretation of digitalization as a threat. However, the 95% CI [-0.04, 0.00[6]] (Table 4) did not indicate significance of this indirect effect because it included zero. The effect of industry digital maturity on employees' interpretation of digitalization as a threat to their organization was negative ($\beta = -0.16$, $p < 0.001$; 95% CI [-0.23, −0.08]; Model 5, Table 3), while the effect of the interpretation of digitalization as a threat on PSD was not significant ($p > 0.10$; 95% CI [-0.03, 0.20], Model 3, Table 2). Hence, we concluded that hypothesis 3 was not supported.

Although CAPS theory led us to focus on indirect effects, we examined whether there was any direct effect of industry digital maturity on PSD for completeness. We found that this link was not significant ($p > 0.10$) and included zero in its 95% CI. In contrast, the total indirect effect of industry digital maturity on PSD was significant ($\beta = 0.04$; 95% CI [0.02, 0.06]). This finding indicates that two employees who work in industries that differ by one standard deviation in industry digital maturity differ by approximately 0.04 standard deviations in their likelihood of proactively developing their skills as a result of the indirect links between industry digital maturity and PSD via interpreting digitalization as controllable, as an opportunity for, and/or as a threat to their organization.

Hypothesis 4 suggested that proactive personality moderates the indirect effect of industry digital maturity on PSD such that the effects of industry digital maturity on individual interpretations of digitalization as controllable (H4a), as an opportunity (H4b), and as a threat (H4c) are stronger at higher levels of proactive personality. However, we did not find that proactive personality moderated any of the links between industry digital maturity and individual interpretations of digitalization;

[5] Precisely, 0.0024.

[6] Precisely, 0.0036.

Table 1
Means, standard deviations, internal consistencies, and correlations of all the variables in the regression model.

		Mean	S.D.	1	2	3	4	5	6
1	PSD (T2)	3.54	1.02	(0.90)					
2	Digital maturity (T0)	10.78	7.49	0.00					
3	Controllability (T1)	3.66	1.06	0.14**	0.24**	(0.94)			
4	Opportunity (T1)	3.88	1.06	0.13**	0.19**	0.58**	(0.96)		
5	Threat (T1)	1.99	1.07	−0.07	−0.16**	−0.54**	−0.77**	(0.95)	
6	Proactive personality (T1)	3.67	0.59	0.19**	−0.01	0.10**	0.15**	−0.14**	(0.76)

Note. $N = 710$. Scales of concepts 1 to 5 ranging from 1 to 5. Cronbach's alpha in parentheses.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

Table 2
Main effects of industry digital maturity and individual interpretations of digitalization on proactive skill development.

	Proactive skill development (T2)		
	Model 1	Model 2	Model 3
Control variables			
Constant	0.00	0.00	0.00
Proactive personality (T1)			0.17***
Main effect			
Industry digital maturity (T0)	0.00	−0.04	−0.03
Mediation effects			
Controllable (T1)		0.12**	0.12**
Opportunity (T1)		0.13*	0.11
Threat (T1)		0.09	0.10
Overall F	0.01	4.83	8.14
R^2	0.00	0.03	0.06
Change in F		6.44***	20.84***
Change in R^2		0.03	0.03
Sample size	710	710	710
Bootstrap samples (max. 5,000)	5,000	5,000	5,000

Note. Beta coefficients reported.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

neither of the interaction effects was significant ($p > 0.10$, Models 2, 4, 6, Table 3), and their 95% CIs included zero. Consistently, the inclusion of the interaction term in our regression models did not lead to a significant change in R^2, as indicated by the tests of highest-order unconditional interactions ($p > 0.10$) implemented in Hayes' (2017) PROCESS macro. Likewise, the 95% CIs of the indices of moderated mediation implemented in Hayes' (2017) PROCESS macro did not point to any significant interaction between industry digital maturity and proactive personality in the prediction of employees' interpretations of industry digital maturity. We therefore conclude that hypotheses 4a, 4b, and 4c were not supported.

Overall, our predictors, i.e., industry digital maturity and employees' interpretation of digitalization, combined explained 3% of the variance in PSD, i.e., 2% over and above proactive personality (which, as a single regressor, explained 4% of the variance in PSD and is regarded as one of

Table 4
Indirect effects of industry digital maturity on proactive skill development (PSD) through individual interpretations of digitalization.

Without proactive personality as control variable				
	Effect	**Boot SE**	**LL 95% CI**	**UL 95% CI**
TOTAL	0.04	0.01	0.02	0.06
Controllable	0.03	0.01	0.01	0.06
Opportunity	0.02	0.01	0.00[a]	0.05
Threat	−0.01	0.01	−0.04	0.00[b]
With proactive personality as control variable				
	Effect	**Boot SE**	**LL 95% CI**	**UL 95% CI**
TOTAL	0.03	0.01	0.01	0.06
Controllable	0.03	0.01	0.01	0.05
Opportunity	0.02	0.01	0.00[c]	0.05
Threat	−0.02	0.01	−0.04	0.00[d]

Note. $N = 710$; bootstrap samples = 5,000.
BootSE = bootstrapped standard error; LL = lower limit; CI = confidence interval; UL = upper limit.
[a] Precisely, 0.0024.
[b] Precisely, 0.0032.
[c] Precisely, 0.0005.
[d] Precisely, 0.0020.

Table 3
Effects of industry digital maturity on individual interpretations of digitalization as controllable, as an opportunity, and as a threat.

	Controllable		Opportunity		Threat	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variables						
Constant	−0.00	0.00	−0.00	0.00	0.00	0.00
Main effect						
Industry digital maturity (T0)	0.24***	0.24***	0.19***	0.19***	−0.16***	−0.16***
Moderation						
Proactive personality (T1)		0.11**		0.15***		−0.14***
IDM*Proactive personality		0.01		0.01		0.01
Overall F	43.25	17.42	26.27	14.93	18.08	10.80
R^2	0.06	0.07	0.04	0.06	0.03	0.04
Change in F		4.31*		8.96***		7.01***
Change in R^2		0.01		0.02		0.02
Sample size	710	710	710	710	710	710
Bootstrap samples	5,000	5,000	5,000	5,000	5,000	5,000

Note. IDM = Industry digital maturity. Beta coefficients reported.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

the most important and consistent predictors of proactive behaviors, cf. Fuller & Marler, 2009). Moreover, industry digital maturity explained 6% of the variance in perceived control, 4% of the variance in perceived opportunity, and 3% of the variance in perceived threat. We also compared the correlation coefficients between our key variables with Bosco, Aguinis, Singh, Field, and Pierce's (2015: Table 5) benchmarking of typical effect sizes of relationships between attitudes/evaluations and extra-role performance. Compared to these values, the correlation between perceived control (attitude/evaluation) and PSD (extra-role performance) can be regarded as medium (falling into the 33rd percentile), and the correlation between perceived opportunity (attitude/evaluation) and PSD (extra-role performance) can be regarded as small-medium (falling between the 25th and 33rd percentiles). Overall, we conclude that the effects found in this study are not very large, which is not unusual for the type of relationships we investigated.

To examine the robustness of our findings, we ran regressions with three distinct specifications as described in the next section.

4.2.1. Robustness checks

Time frame of PSD. Repeating the previously described regression models using the two broader timeframes for PSD (namely, "since the beginning of 2020" and "in 2019"), we found that these two broader timeframes of PSD did not change the results regarding our hypotheses.

Controlling for industry effects in addition to industry digital maturity. To control for industry effects in addition to industry digital maturity, we conducted all the analyses of our hypotheses with standard errors clustered for industry in Stata 15 (StataCorp, 2017). The resulting coefficients of most of our independent variables of interest did not change in significance and direction. The only change in significance was that the coefficient of the relation between industry digital maturity and individual interpretation of digitalization as a threat was significant at the 0.01 level but not at the 0.001 level ($p < 0.01$; its 95% CI still excluded zero).

Controlling for proactive personality. Following Spector and Brannick's (2011) suggestions regarding the use of control variables, we additionally investigated the influence of proactive personality on our first three hypothesized relations (H1 to H3) because proactive personality has been shown to drive behaviors similar to PSD (e.g., other proactive behaviors, Seibert et al., 2001; Orvis & Leffler, 2011; and self-directed learning, Fuller & Marler, 2009; Raemdonck, van der Leeden, Valcke, Segers, & Thijssen, 2012), and proactive personality may influence individual perceptions of situational attributes (recently, e.g., Debus, König, Kleinmann, & Werner, 2015; Sherman, Rauthmann, Brown, Serfass, & Jones, 2015).

The results of these analyses indicated that the effect of industry digital maturity on employees' perceptions of control as well as the effect of perceived control on PSD did not change in significance or direction when controlling for proactive personality (Model 2, Table 3; Model 3, Table 2; cf. hypothesis 1). Similarly, controlling for proactive personality did not seem to influence the link between industry digital maturity and employees' perception of opportunity (Model 4, Table 3; cf. hypothesis 2). However, the effect of opportunity perception on PSD (cf. hypothesis 2) lost significance ($p > 0.05$, Model 3, Table 2), and its 95% CI [-0.01, 0.23] did not exclude zero when controlling for proactive personality. Finally, the effect of industry digital maturity on employees' threat perception and the effect of perceived threat on PSD did not change in significance and direction when controlling for proactive personality (Model 6, Table 3; Model 3, Table 2; cf. hypothesis 3).

Adding control variables. Consistent with Spector and Brannick's (2011) recommendations on using control variables, we repeated all regressions with (proactive personality and) control variables.[7] Specifically, we added age, highest educational degree (1 = bachelor, 0 = master or equivalent), final grade (with grades ranging from a high of 1.0 to a low of 3.4), actual number of working hours (minimum 7, maximum 75) and dummy variables for job level (lower, middle, and upper management; specialist leader, e.g., project manager) to our regression models. We chose these control variables because previous research has shown that these or similar individual- and organizational-level factors may influence both individual learning behaviors (e.g., Cerasoli et al., 2018; Claes & Ruiz-Quintanilla, 1998; Edmondson, Boyer, & Artis, 2012; Pajic et al., 2018) and interpretations of work environments (e.g., Musteen, Liang, & Barker III, 2011; van Emmerik, Bakker, & Euwema, 2009).

The data from 570 participants support our conclusions regarding our hypotheses. Specifically, the effects of industry digital maturity on the three interpretations of digitalization examined did not change in significance or direction after including these control variables. By examining these control variables, we found that having a specialist leader position (compared to a nonleadership position) inhibited perceived threat.

Similarly, the effects of perceived control and threat on PSD did not change in significance or direction after including proactive personality and these control variables in the respective regression models. However, the effect of perceived opportunity on PSD became nonsignificant in the regression models with the control variables. Notably, we found that the highest educational degree, actual number of working hours, occupying a specialist leader position (compared to a nonleadership position), and having an upper management position (compared to a nonleadership position) significantly supported PSD. In summary, we conclude that the main findings described in the previous section are robust, except for the link between perceived opportunity and PSD.

Findings from a similar sample. Notably, hypothesis testing in a preliminary study using cross-sectional data collected in 2016 and 2017 from a different cohort of higher education graduates with similar characteristics in terms of work experiences, education, age, and distribution of sex and industry of current employment yielded the same results as the present analyses in terms of the significance and direction of the effects. A difference was observed in the post hoc tests such that in the cross-sectional sample, we found a significant direct effect of industry digital maturity on PSD ($\beta = 0.08$, $p < 0.05$), which became nonsignificant ($\beta = 0.01$, $p > 0.10$) after we added the variables of our indirect effects, i.e., individual interpretations of digitalization as controllable, as an opportunity and as a threat, to the model, with a subsequent significant change in F ($\Delta F = 23.68$, $p < 0.001$, $\Delta R^2 = 0.09$).

5. Discussion

We recognize the importance of employees' self-initiated skill development at work, particularly in the face of digital transformation. Hence, we developed and tested a model that proposes that industry digital maturity has a positive indirect effect on employee PSD via employees' interpretations of digitalization as controllable, as an opportunity, and as a threat to their organization. Furthermore, we proposed that proactive personality strengthens the indirect effects of industry digital maturity on PSD by supporting the effects of industry digital maturity on employees' interpretations of digitalization.

Consistent with our expectations, we found that industry digital maturity facilitates employees' interpretations of digitalization as controllable and as an opportunity for their organization and, in turn, employee PSD. However, our robustness checks suggested that the indirect effect of industry digital maturity on PSD via opportunity perception (specifically, the link between opportunity perception and PSD) may be driven by proactive personality. Thus, the indirect effect between industry digital maturity and employees' PSD via opportunity perception seemed to be less robust than the effect via perceived controllability.

In contrast to our hypothesis, we did not find an indirect relation between industry digital maturity and PSD via perceived threat.

[7] The regression tables of these analyses are available upon request from the authors.

Specifically, our results support the expected negative link between industry digital maturity and employees' interpretation of digitalization as a threat, but no relation was observed between threat perceptions and PSD. This latter finding seems to contradict previous research suggesting that fear concerning the continued existence of one's job inhibits proactive behaviors (Dutton et al., 1997; Klehe et al., 2011). Nonetheless, explanations for this unexpected result might be that interpretations of macrolevel cues as threatening for an organization are not always associated with fear for one's own job. Furthermore, this finding seems to be consistent with the threat-rigidity hypothesis, which proposes that employees tend to behave routinely in the face of threat (Staw, Sandelands, & Dutton, 1981), as well as a study by Strobel and coauthors (2017) showing that employees' proactive strategic behavior is driven more by promotion-focused motivation (i.e., seeking to achieve gains) than by prevention-focused motivation (i.e., seeking to avoid losses).

Moreover, our results support the use of an additive person-environment model rather than interactions between proactive personality and industry digital maturity in the prediction of employees' interpretation of digitalization. Following CAPS theory (Heslin et al., 2019; Mischel & Shoda, 1995), a potential explanation could be that the situational cue of industry digital maturity might be thematically not connected (enough) with proactive personality. Specifically, we found that proactive personality has positive direct effects on individual interpretations of digitalization as controllable and as an opportunity and a negative relation between proactive personality and individual interpretations of digitalization as a threat.

In summary, our findings indicate employees' interpretations of macrolevel developments as mechanisms in the link between industry maturity in handling these developments and employees' PSD. At a more general level, in line with CAPS theory (Heslin et al., 2019; Mischel & Shoda, 1995, 2010), our findings indicate that macrolevel contexts may translate into individual proactive career behavior via individual interpretations of the possible consequences of current macrolevel developments for an employing organization.

5.1. Theoretical contributions

The findings of the present study contribute to previous research on the predictors of self-initiated skill development among employees (e.g., Bednall & Sanders, 2017; Ren & Chadee, 2017; Strauss & Parker, 2018; Taber & Blankemeyer, 2015), the role of context in microorganizational behavior (Johns, 2018), and the consequences of digital transformation for the management of organizations (e.g., Cascio & Montealegre, 2016; Colbert et al., 2016; Sousa et al., 2019a).

First, to contribute to research on the predictors of self-initiated skill development (e.g., Noe & Ellingson, 2017; Strauss & Parker, 2018; Ren & Chadee, 2017; Sousa & Rocha, 2019b), the results of this study indicate that PSD may depend on how employees evaluate developments in the extraorganizational environment. Furthermore, the results of this study suggest that these evaluations may depend on industry maturity in handling these macrolevel developments. Hence, this study points to individual perceptions of and subsequent reactions to current developments in organizations' broader environments (cf. Heslin et al., 2019; Mischel & Shoda, 1995, 2008, 2010; Williams & Wood, 2015) as a relevant additional focus for research on self-initiated skill development.

Second, following Johns' (2018) suggestions for future research concerning contextual effects on organizational behavior, we investigated how a more distal, omnibus contextual cue—namely, a technology-driven trend—translates into individual behavior. This analysis expands our knowledge of the nature of contextual cues that should be considered when examining employee behavior: Previous literature on person-situation interactions has examined mostly within-organizational cues as predictors of individual behavior (Tett & Burnett, 2003). In contrast, our findings point to situational cues that exist outside organizations as interesting antecedents of employees' perceptions and subsequent behavior.

Third, our findings contribute to the growing stream of research on the implications of digital transformation for organizations and their members: This study identifies links between industry digital maturity, individual interpretations of digitalization, and subsequent individual behavior. Hence, this study suggests research on the effects of digital transformation on individual behavior, particularly individual skill development, as an interesting additional field for research in organizational behavior on the way we work, lead, and do business (Cascio & Montealegre, 2016; Wong & Fieseler, 2018) and the development of individual competence needs (Sousa & Rocha, 2019a; van Laar et al., 2017).

5.2. Practical implications

Our study has practical implications for organizations that aim to support skill development among their employees, especially in the context of ongoing digital transformation. Our findings suggest that industry maturity in handling technology-driven developments is positively associated with employees' perceptions of these developments as controllable and as an opportunity and is negatively related to employees' perceptions of such developments as a threat. Furthermore, our results indicate that employees' perceptions of technology-driven developments as controllable and as an opportunity have the potential to support PSD among employees.

Hence, to promote skill development among employees, organizational managers could deliberately design employee communications on the consequences of macrolevel trends (such as digitalization) for their organization. In this regard, they could refer to the actions used by comparable organizations and industries to manage these trends. This may influence employee perceptions and thus may support managerial communication goals of facilitating individual self-initiated skill development. Because our study focuses on recent higher education graduates, our results may be of particular relevance for designing HR practices targeting this group of employees. For example, considering our results, programs that aim for the development and retention of "generations Y and Z" might include discussions of how the employing organization may benefit from ongoing macrolevel trends and developments to strengthen employees' perceptions of such developments as an opportunity and as controllable for the organization. Based on the results of our study, this may strengthen employees' willingness to proactively and continuously enhance their knowledge and skills.

Notably, the results of our robustness checks suggest that proactive personality may play a role in the positive relation between employees' opportunity perception and PSD but not in the positive link between employees' control perception and PSD. Hence, designing organizational communication strategies aimed at facilitating employees' interpretations of controllability rather than of opportunity may be most effective in enhancing PSD among a broad variety of employees.

5.3. Limitations and suggestions for future research

This study has some limitations that may be addressed in future research.

Causality. Although the findings of this study are based on archival and temporally separated primary data consistent with the temporal sequence presumed in our research model, this study does not provide clear evidence of causal relations. For instance, we do not know how long to expect employee perceptions of technology-driven trends to cause PSD. Hence, it is still possible that our temporally separated study design erroneously points to causal relations (Spector, 2019). Nevertheless, our study design provides evidence for three (of four) elements of making a case for causality (Spector, 2019). First, we establish relations between industry digital maturity (a rarely examined macrolevel cue in organizational behavior), employee interpretations of macrolevel cues, and PSD. Second, we rule out alternative explanations for covariation through the use of control variables at the individual and organizational levels (namely, proactive personality, age, previous learning experiences, actual number of working hours, and job level). Third, we provide a previously unknown explanatory mechanism for the link between industry digital maturity and PSD or for the translation of macrolevel factors into microbehavior. We encourage further studies using experimental study designs and longitudinal study designs with repeated measures at three or more time points (cf. Ployhart & Vandenberg, 2010) to further corroborate causality and explore the temporal dynamics of PSD.

Common method variance. We cannot fully rule out problems of common method variance because our mediator, moderator, and dependent variables stem from self-report survey data and our mediator and moderator variables were assessed at the same time point using the same questionnaire. However, we investigated PSD among employees, a voluntary behavior that is not always fully known by colleagues or supervisors (Orvis & Ratwani, 2010). Furthermore, other-ratings of employee proactivity may include observational or egocentric biases (Parker, Williams, & Turner, 2006). In these cases, self-ratings rather than other-ratings have been argued to be advantageous (Orvis & Ratwani, 2010; Parker et al., 2006). Moreover, we separated our data collection temporally and employed analytical methods (as suggested by Podsakoff et al., 2003) to reduce the likelihood of common method bias. Nevertheless, we support the suggestion of Ren and Chadee (2017) to collect data from multiple sources to avoid biases resulting from self-report, such as data from colleagues and supervisors.

Constraints on generality. Following the suggestions by Simons, Shoda and Lindsay (2017), we refer to participants, materials, procedures, and temporal specificity in this "constraints on generality" statement. As noted above, this study examines higher education graduates (mostly without any migratory background) approximately 1.5 and 3.5 years after obtaining their degree from a German university. We expect that our findings with this sample generalize to other highly qualified early career professionals who have worked for approximately six years in their current firm. However, given that national culture (Hofstede, 1991) might influence PSD (Claes & Ruiz-Quintanilla, 1998), our findings might hold only for cultures that rate similar to the German culture on Hofstede's (1991) dimensions (especially masculinity/femininity and uncertainty avoidance). Furthermore, as job type and employment experiences might influence PSD (Claes & Ruiz-Quintanilla, 1998), our results might not hold for less qualified or more professionally experienced participants.

To directly replicate our findings, researchers could conduct online surveys using the same scales that we applied to assess PSD and employees' interpretations of digitalization. At the beginning of the survey, they would assure their survey participants that their participation is voluntary, that in case of nonparticipation, they would not suffer any disadvantages and that their data would be treated pseudonymously, complying with the General Data Protection Regulation of the European Union and the Bavarian Data Protection Act. Furthermore, researchers would use the same external data on industry digital maturity (Rammer et al., 2017) to replicate our findings. However, as digital transformation changes organizational and industry technological standards (Cascio & Montealegre, 2016), it might be fruitful for future studies to adapt the indicator of industry digital maturity used by Rammer and coauthors (2017) so that they gain sufficient variance in data on the dissemination of digital technologies within industries. Consistent with Simons and coauthors (2017: 1126), we conclude that "we have no reason to believe that the results depend on other characteristics of the participants, materials, or context".

Additional suggestions for future research. Because employees are nested in industries (and, depending on the survey design, also in firms), an interesting path for future research might be to examine variances within and between levels (e.g., the individual, firm, and industry) as well as the interactions between levels further detailed by running multilevel analyses (e.g., Hox, Moerbeek, & van de Schoot, 2018). Additionally, to enhance our understanding of the role of context as a driver of employee skill development, we encourage future research to systematically examine different types of situational cues (e.g., proximate versus distal, omnibus versus discrete, and social versus task based; Johns, 2018), including information regarding employees' job type (e.g., occupation), as predictors of skill development. Furthermore, establishing benchmarks for evaluating the effect sizes of macro–micro relationships (including indirect effects) comparable to those we examined appears to be a valuable aim for future research (cf. Bosco et al., 2015). In this aim, consistent with Barnes, Dang, Leavitt, Guarana, and Uhlmann (2018), we encourage researchers to exploit archival data from macrolevel contexts and connect such data with individual-level survey data. Moreover, future studies may benefit from examining why some evaluations of a context facilitate skill development while others do not. Specifically, these studies could identify the mechanisms that explain which particular interpretations predict skill development (in addition to controllability, opportunity and threat—for instance, complexity, familiarity, feasibility, and urgency; Dutton et al., 1989).

6. Conclusion

In line with CAPS theory, the results of this study suggest that macrolevel, technology-driven developments may influence employee PSD indirectly via employees' interpretations of the possible consequences of these developments for their organization. Specifically, we find positive indirect effects of industry digital maturity on employee PSD via interpretations of digitalization as controllable and as an opportunity for their employing organization. Because employee skill development is increasingly needed, especially in the context of dynamic macrolevel developments, we encourage further studies that expand our knowledge of how developments in the broader organizational environment influence individual skill development.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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