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The Influence of Mental Models on Employee-Driven Digital Process Innovation during Times of a Crisis

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Abstract

Digital technologies democratise the development of digital innovation. The resulting employee-driven digital innovation has become a major driver for digital transformations and especially important during crisis times, such as the COVID 19 pandemic. To better understand cognitive factors influencing employee-driven digital process innovation (EDPI), we investigate the role of individual mental models for EDPI during times of a crisis compared to 'normal' times. Drawing from longitudinal data before and during the COVID 19 crisis, we find mental models having a significant influence on EDPI behaviour during 'normal' times. This relationship, however, loses robustness during the crisis, when employees with more accurate mental models show significant less EDPI behaviour before slowly recovering. We relate these findings to the mental models' explanatory power and derive recommendations for management. Our study contributes explanatory knowledge on employee-driven digital innovation and related cognitive antecedents.

Keywords: Employee-Driven Innovation; Employee-Driven Digital Innovation; Digital Innovation; Process Innovation; Mental Model; Cognitive Antecedent

Introduction

Digital technologies fuel innovation at an unprecedented speed and on an unprecedented scale (Kohli and Melville 2019). The characteristics of digital technologies democratise the development of innovation in general and digital innovation in particular (Drechsler et al. 2020; Kreuzer et al. 2022). This means that an organisation's employees are asked as well as enabled to contribute to digital innovation (Hevner and Gregor 2020) in the context of their work beyond centralised units, i.e., defined as employee-driven digital innovation (Høyrup 2010; Kesting et al. 2016; Opland et al. 2020; Opland et al. 2022). Exemplary activities of employee-driven digital innovation include idea generation, idea promotion, and idea implementation (van Zyl et al. 2021).

The ongoing COVID 19 pandemic has accelerated the need for digital innovation initiatives (Fletcher and Griffiths 2020) and, thus, increased the importance of employee-driven digital innovation. Specifically, the focus on employee-driven digital process innovation (EDPI) is crucial in such a crisis situation as the success of internally focused digital innovation and transformation initiatives depends upon an organisation's employees who know process optimisation and innovation potential in their daily routines best and who should be motivated to leverage digital technologies to find better ways of performing tasks (Osmundsen et al. 2018). Further, employees' resistance is a relevant barrier to digital transformation success, that can be addressed by involving employees, for example, through EDPI (Svahn et al. 2017). To date research on employee-driven digital innovation has mainly focused on the digital innovation outcomes (e.g. van Zyl et al. 2021); or the use of digital tools to support employee-driven innovation behaviour (Huesig and Endres 2019; Lahtinen et al. 2017). Beyond that, Opland et al. (2022) emphasize that further research on the pre-conditions for employee-driven digital innovation is needed, where cognitive factors play an important role.

With regards to cognitive factors influencing employee innovation behaviour, we have already gained some insights from non-digital-specific research in terms of dispositional antecedents (e.g., openness, creativity, self-efficacy) as well as contextual antecedents (e.g., job characteristics, leader, climate for innovation driving individual innovation behaviour) (Janssen 2000; Janssen 2005; Ramamoorthy et al. 2005; Scott and Bruce 1994; Wu et al. 2014). In times of a crisis dispositional cognitive factors gain importance, as uncertainty increases and as contextual antecedents often cannot be influenced (e.g., physical distancing and remote work was mandatory for most employees during the first phases of the COVID 19 pandemic) (Kiss and Österholm 2020). With a focus on dispositional cognitive factors, for example, Wu et al. (2014) found employees' need for cognition (i.e., a dispositional tendency to engage in and enjoy thinking) to be positively associated with individual innovation behaviour. Ramamoorthy et al. (2005) showed direct effects of a perceived obligation to innovate on individual innovation behaviour. Beyond these relevant insights, research has shown a crucial role of mental models driving employees' individual innovation behaviour (Doyle et al. 1998). Mental models are described as small-scale representations of reality in humans' minds (i.e., imagination of the work processes and corresponding innovation potential) which stimulate EDPI behaviour to create new or enhance existing processes through digital technologies (Craik 1943; Furlough and Gillan 2018; Gary and Wood 2011; Norman 1983). To date, however, the influence of mental models as cognitive antecedents of EDPI is understudied and hardly understood.

The purpose of this work is to expand our understanding of the cognitive antecedents of EDPI comparing the influence of mental models on EDPI behaviour during times of a crisis with their relationship during 'normal' times. Specifically, we build on empirical insights collected before and during the COVID 19 pandemic as an example of a health-related crisis. A deeper understanding of the role of individual mental models for EDPI is of high importance as individual pre-conditions for employee-driven digital innovation are currently underplayed in existing (digital) innovation research (Opland et al. 2022). Against this backdrop, and based on longitudinal data covering individual mental models and EDPI behaviours before and during the Corona crisis over one year, we ask the following research question:

How do employees' mental models influence EDPI behaviour during a crisis compared to 'normal' times?

To address this research question, we adopt mental model theory to develop a research model on the influence of individual mental models on EDPI behaviour. We apply this model to data collected from more than 200 employees engaged in operational (i.e., not leadership) activities, before and at several points during the Corona crisis – as an exemplary health-related crisis – revealing that mental models have a significant influence on EDPI behaviour in 'normal' times. However, we also show that, during the crisis, this relationship loses robustness: While the EDPI behaviour of employees with less accurate mental models has remained stable, employees with more accurate mental models have engaged significantly less in EDPI at the beginning of the crisis before slowly recovering one year after, showing a quadratic relationship. We discuss how these findings may further our understanding of dispositional cognitive antecedents of innovation behaviour in general and the influence of mental models on EDPI in particular. Thereby, our study contributes to Information Systems (IS) knowledge by illuminating the cognitive drivers of EDPI in times of a crisis compared to 'normal' times showing a longitudinal development. We also discuss implications for practitioners, i.e., providing managers with valuable insights on mental models as cognitive antecedents driving their operational employees' EDPI behaviour as well as giving managerial guidance on how to best address employees with more or less accurate mental models in 'normal' times compared to times of a crisis.

Background

Employee-driven Digital Process Innovation

The rapid emergence and adoption of digital technologies not only drive digitalisation at individual and societal levels (Berger et al. 2018; Legner et al. 2017), but also the digital transformation of all kinds of organisations (Drechsler et al. 2020; Vial 2019). Research has put a major focus on digital process innovation (Van Looy 2021) that is a relevant element of digital transformations (Bogéa Gomes et al. 2020) and refers to 'significantly new (from the perspective of the adopter) ways of doing things in an organisational setting that are embodied in or enabled by IT' (Fichman et al. 2014, p. 334). The resulting creation of new processes or the substantial transformation of existing processes (Peng et al. 2008) is essential for improving an organisation and enhancing its competitive performance (Van Looy 2021). Examples of digital process innovation include warehouse automation systems to increase productivity, and digital platforms to enhance ideation processes (Fichman et al. 2014).

At the same time, the characteristics of digital technologies (i.e., re-programmability, homogenisation of data, self-referential nature) facilitate the democratisation of innovation, enabling almost anyone to contribute (Drechsler et al. 2020; Kreuzer et al. 2022). As a result, organisations can leverage the innovative resources (i.e., knowledge, experience, and creativity) of their employees for EDPI in the context of their work environment as essential drivers of digital innovation and digital transformation (Pavlou and El Sawy 2011). Involving employees in digital innovation is a very different innovation approach compared to centralised R&D units (Haapasaari et al. 2018). Bäckström and Bengtsson (2019) point out that only limited attention has, so far, been given to employee-driven innovation in general, whereas Opland et al. (2020) find 13 studies on employee-driven digital innovation with various foci, but few quantitative studies. Among the few, Kesting et al. (2016) examined the effect of employee participation on innovation in China providing evidence on the explanation power of the 'western concept' of employee-driven innovation outside the western world. Further, Huesig and Endres (2019) explored the role of functionality in the adoption of innovation management software by innovation managers. More generally, Opland et al. (2022) studied the intersection between employee-driven innovation and digital innovation finding, among others, the need for more research into the preconditions (e.g., antecedents) for employee-driven digital innovation.

Building on the research stream highlighted by Høyrup (2010), Opland et al. (2020), and Opland et al. (2022) our definition of EDPI refers to employees' innovation behaviour that leads to the creation of digital process innovation in their work environment embodied or enabled by the use of digital technologies. More specifically, we understand EDPI as innovation behaviour at work (Janssen 2000; Wu et al. 2014) by ordinary employees (Krejci et al. 2021) that relates to the generation, adoption, and implementation of new ideas (Scott and Bruce 1994) regarding enhanced or novel processes through digital technologies. In this regard, *idea generation* describes the recognition of problems and/or opportunities in a process and the development of (digitalisation) ideas that change and improve the said process (Calantone et al. 2002). *Idea championing* refers to activities that support the *idea adoption*, e.g., by promoting innovation ideas among colleagues to achieve a sufficient mass of 'believers' who will support subsequent *idea implementation* (de Jong and den Hartog 2010). A result of EDPI could be, for example, the automation of time-consuming and/or costly individual activities by means of robotic process automation (Hofmann et al. 2020).

Mental Models as Antecedents of Individual Employee-Driven Digital Process Innovation Behaviour

Generally, research on individual innovation behaviour distinguishes dispositional antecedents (e.g., openness, creativity, self-efficacy) as well as contextual antecedents (e.g., job characteristics, leader, climate for innovation) driving individual innovation behaviour (Janssen 2000; Janssen 2005; Ramamoorthy et al. 2005; Scott and Bruce 1994; Wu et al. 2014). In this work, we take a cognitive, dispositional perspective and adopt mental model theory (Holyoak and Cheng 2011; Mohammed et al. 2010) to examine how EDPI is influenced by individual mental models.

Research on mental models has a long history (Doyle et al. 1998) which can be followed back to the work of Craik (1943) on *The Nature of Explanation*. In this book, he referred to mental models as small-scale models of reality in humans' minds which are used to solve problems in their environmental context (Craik

1943; Furlough and Gillan 2018). Later Norman (1983) understood these small-scale models as representations of the systems with which humans interact and which "provide predictive and explanatory power for understanding the interaction" (p.7). Thereby, a mental model can be conceptual or propositional (Doyle and Ford 1998) as well as image-like (Rouse & Morris, 1986). In other words, mental models describe one's subjective view of observed system relations, potentially being used by a person to take innovation actions and show innovation behaviour (Gary and Wood 2011).

Originating in psychology-related research (Holyoak and Cheng, 2011; Mohammed et al., 2010), mental models have found their way into IS research (e.g. explaining the effects of information presentation; Kelton et al. 2010; Shaft and Vessey 2006; Vessey 1991), where, for example, Shaft and Vessey (2006) refer to mental representations of software and modification tasks that drive software comprehension and performance on a modification task. Various experimental research has observed that increased accuracy of individuals' mental models has a positive impact on individual decision-making performance (Davis and Yi 2004; Gary and Wood 2011; Kelton et al. 2010; Ritchie-Dunham et al. 2007). The reasons for this are not only that actions will be better processed, cognitively, but that the individual also has more "explanatory power for understanding" (Norman 1983, p. 7) to improve the respective situation (Weick 1995; Zohar and Luria 2003). Specifically, more accurate mental models allow individuals to better understand how elements are connected, to anticipate potential shortcomings, and, to see more sense in engaging in activities that help to align reality with their ideal view, as represented in the mental model (Steigenberger 2015).

In the field of employee-driven innovation, prior research has examined behavioural drivers, barriers, and implications, e.g., the role of job types and sub-sectors (Bysted and Hansen 2015), the role of inclusiveness in driving innovation behaviour (Bäckstöm and Lindberg 2018), and the negative relationship between stress and innovation behaviour (Van Dyne et al. 2002). Further, the role of understanding the related environment has been highlighted as relevant factor influencing EDPI (Leyer et al. 2021). However, the specific role of mental models and their influence as antecedents on EDPI – especially during times of a crisis – has, so far, not been addressed.

Research Model and Hypotheses

Figure 1 depicts our research model accounting for mental model as the cognitive antecedent of EDPI behaviour and the influence of a crisis (i.e., in this case the COVID 19 pandemic) on this relationship. As outlined, the contributions that individual, operational employees make to digital process innovation in the context of their work environment are essential drivers of digital innovation and digital transformation (Drechsler et al. 2020; Kreuzer et al. 2022; Pavlou and El Sawy 2011). Therefore, we investigate such *EDPI behaviour* as the outcome (i.e., dependent) variable of our model.

Given the theoretical underpinning of the general relationship between individual mental models and behaviour, we are interested in studying the influence of *mental models regarding process digitalisation* as cognitive antecedent of *EDPI behaviour*. Specifically, we follow the understanding of Craik (1943), Furlough and Gillan (2018), Gary and Wood (2011), and Norman (1983) defining mental models as small-scale representations of reality in humans' minds (i.e., imagination of the work processes and corresponding innovation potential) which provide explanatory power for understanding systems' relations and for taking actions, i.e., showing EDPI behaviour to create new or enhance existing processes through digital technologies. Individuals who imagine and understand work processes and related innovation opportunities better, have less difficulties imagining related digital innovation and, thus, their cognitive effort is presumably lower (De Neys 2017). As a consequence, such individuals are presumably more efficient and effective when investing time and cognitive resources in digital innovation activities. Further, existing research insights reveal that an increased accuracy of individuals' mental models impacts behaviour such as decision making, e.g., decision-making performance, which assumes that the mental model drives behavior shown (Davis and Yi 2004; Gary and Wood 2011; Kelton et al. 2010; Ritchie-Dunham et al. 2007). Against this backdrop, we formulate the first hypothesis regarding a general relationship of both variables in 'normal' times:

H1: *The mental model re. process digitalisation is positively related to EDPI behaviour in 'normal' times.*

It is, however, important to note that a good imagination and understanding of a context reflected in an accurate mental model not necessarily leads to actions, e.g., observed by high performance (Gary and Wood 2016). This is rooted in the knowledge-behavior gap, a phenomenon that describes that having the knowledge about something does not necessarily lead to the respective behavior, which is influenced by certain contextual factors (Rimal 2000; Tichenor et al. 1970). With regards to the influence of the COVID 19 pandemic as an exemplary health-related crisis, we argue that it is unclear how the relationship between the mental model regarding process digitalisation and EDPI behaviour is affected, accounting for a potential knowledge behaviour gap. The Corona crisis has significantly altered the conditions facing of the global workforce, as, for example, remote working has become the new norm for many employees under severe private and business limitations and uncertainty (Kraus et al. 2020). However, in many countries the majority of employees did not suddenly lose their jobs, but could continue working (e.g., in short-time work) from home (Kozicki and Gornikiewicz 2020; Lambovska et al. 2021). As many businesses found their operations hampered, digital solutions such as video conferencing and digital interaction tools became more important, increasing the need for the development of innovative digital processes (Pan et al. 2020). During the Corona crisis, however, conditions for employees and business opportunities for companies changed from one lockdown to another – not only in Germany but in various countries around the world. As a result, crisis-related (digital) opportunities and threats evolved simultaneously (Bar Am et al. 2020) implying that individuals had a stressful time and focused more on the present instead of the future. As a consequence, we argue that due to opposing effects (i.e., rapidly changing work conditions hampering the imagination of EDPI behaviour's potential impact and the emergence of novel, digital innovation opportunities fostering it) it remains unclear how the relationship between the mental model regarding process digitalisation and EDPI behaviour is characterised over time during the ongoing crisis situation. Hence, we hypothesise that a crisis has an effect on the relationship over time, but that it cannot be determined a-priori:

H2: *The relationship between the mental model regarding process digitalisation and EDPI behaviour is changing over the time of a crisis.*

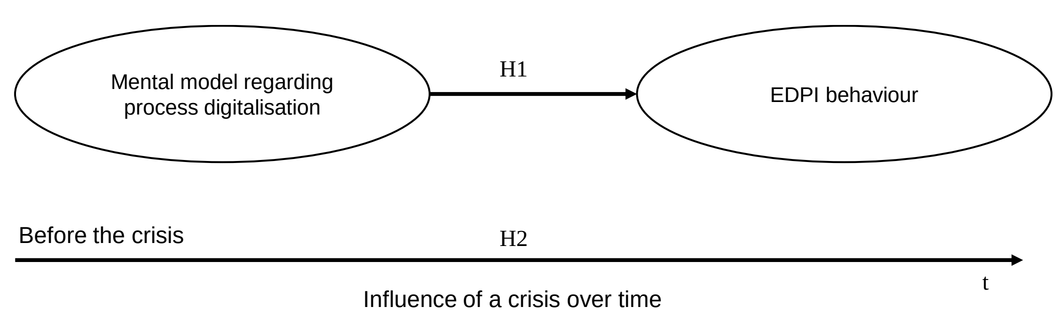

Figure 1. Conceptual research model

Research Method

Participants and Procedure

We collected data using the crowd-sourcing platform *Clickworker* (similar to Amazon MTurk): an unsupervised online platform that offers paid survey services. When using this platform, we followed the recommendations by Goodman et al. (2012) to use a short survey enriched with attention-checking questions. As our interest centred on EDPI aspects, we used filter questions to identify and exclude participants in managerial positions, to ensure that our sample only included employees engaged in operational tasks (in line with Krejci et al. 2021). Similarly, we only included employees working in companies with more than 50 employees (medium-sized) to ensure they encountered a sufficient number of colleagues/processes (sufficient complexity) to be able to report on mental models of the work processes and corresponding innovation potential and their individual innovation behaviour. Since, we had a repeated measurements approach to capture the relationship of the variables over time before and during a crisis (i.e., the COVID 19 pandemic), we selected four points in time for measurement: Before the crisis in March 2020 (T0), early within the crisis during the first lockdown in Germany in April 2020 (T1), 7 months within the crisis in October 2020 (T2) and one year within the crisis in March 2021 (T3). The points in time were chosen to first cover an early impression within the crisis and then to provide a sufficient amount of time (around 6 months each) to allow for a trend indication and to minimize drop-out rates for each measurement. As such, we split the hypothesis H1 into H1.1 to H1.4 to enable an accurate testing for each point in time (see measurement model in Figure 2). In addition, we measured mental model regarding process digitalisation in T3 to control for potential changes within a year's time. Finally, to ensure a sufficient data quality, we also repeated the questions regarding industry, organizational area and company size to ensure that the participants were reporting adequately and not pretending.

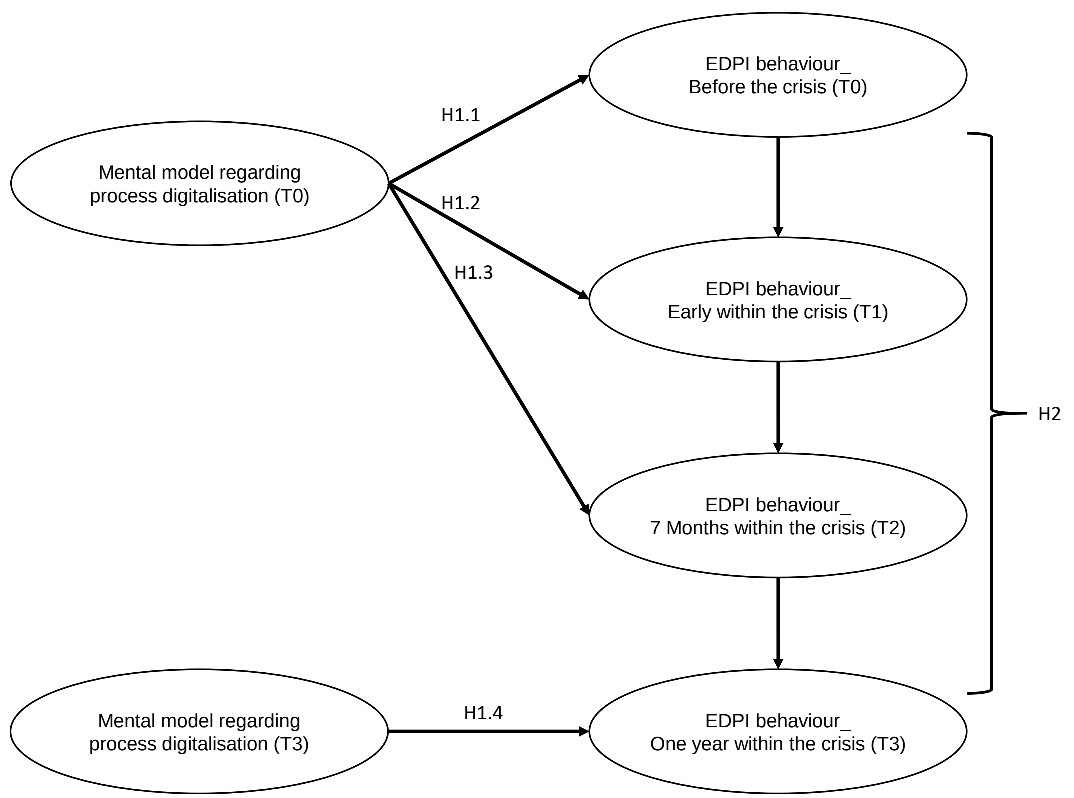

Figure 2. Measurement model over time before and during a crisis

To gather data in the different points in time, we questioned the 395 German participants of our first round of data gathering (reporting on their behaviour before the crisis in March 2020) repeatedly over a time period of one year. The numbers of participants per round were as follows: 211 of the 395 participated in the second round (reporting on their behaviour six weeks later during the first Corona lockdown in Germany)[1], 151 participants responded in the third round that was conducted in October 2020 after a longer summer period with less restrictions and 130 participated one year after (in March 2021) the questionnaire after a time of high restrictions and increasing case numbers in Germany.

[1] We compared the values of MMs and EDPI behaviour of participants between the different questionnaires with the ones who dropped out over time and did not find any differences: EDPI T0: $T(299) = .289$, $p = .773$, EDPI T1: $T(132.92) = -.790$, EDPI T2: $T(151) = .075$, $p = .940$; MM T0: $T(299) = .872$, $p = .384$; MM T1: $T(213) = .270$, $p = .787$; MM T2: $T(151) = -.513$, $p = .609$. Hence, there is no bias present due to participants not answering on an ongoing basis.

We tested our research model regarding H1 using partial least squares (PLS), applying SmartPLS 3.3.3 with 5,000 bootstrapping resamples (Hair et al. 2011). PLS was chosen because our intent was not to measure the fit of our theoretical model with our data, but rather to contribute to the explanation of our dependent variable (i.e., EDPI behaviour). Therefore, construct-based 'performance' criteria, such as R2, are more useful than overall model fit criteria (such as RMSEA or RMR) (Petter 1999). In order to test H2, we applied a repeated measurements analysis of variance (RMANOVA) of EDPI behaviour in addition using the four points in time (T0-T3).

Measures

The variables of our research model were measured reflectively as well as formatively using 5-point Likert scales. Measuring the mental model regarding process digitalisation covers formative dimensions based on objects/actors in the work environment, following the general ideas of Davenport (1993). For measuring EDPI behaviour we adapted the scale from Leyer et al. (2021) for measuring EDPI in a reflective way which is the only one available in literature that incorporates the conceptual aspects *of idea generation, idea championing* and *idea implementation* (see Background Section on *Employee-driven Digital Process Innovation*). It however summarizes adapted prior scales from literature following Calantone et al. (2002), de Jong and den Hartog (2010), Lewis and Seibold (1993) and Robertson (1967). To this, we added *attitude towards EDPI* (measured in T0 and T3), *industry, organisational area, company size* as control variables and *actual working time during the crisis, relative working time in the home office*, and *physical presence at the workplace* for T1, T2 and T3. All items are listed in Appendix A-1.

Results

Validity and Reliability

Standard procedures for checking the validity and reliability of scales (Hair et al. 2011) revealed no issues with our measures: Composite reliability is above the threshold of 0.7 for each variable, indicators' loadings are greater than 0.7, AVE values are all well above the 0.5 threshold, and HTMT values are all below the threshold of .90. We also conducted a finite mixture (FIMIX) segmentation analysis, which indicated that there was no issue with data heterogeneity. Regarding the quality of our structural model, we calculated standardised Stone-Geisser Q2 values, which are positive for each variable and confirm a strong overall prediction power (Henseler et al. 2009). Moreover, the standardised root mean square residual (SRMR) return values below the threshold (.10) of 0.059 for the SRMR composite factor model and .094 for the SRMR common factor model.

As we asked respondents in T0 and T3 regarding the independent and dependent variables at the same time, common method bias/variance might have occurred (Fuller et al. 2016). Our first step in assessing the likelihood of bias/variance was to employ the Harman (1967) single-factor test. The results showed that the first factor only accounted for T0: 34.85% (T3: 27.96%) of the total variance. Secondly, we carried out the test developed by Podsakoff et al. (2003), which showed that, on average, the constructs explain T0: 62.62% (T3: 69.13%) of the variance in our sample. In contrast, the method factor explains on average T0: 2.38% (T3: 2.15%) of the variance, which results in a ratio of substantive variance to method variance of T0: 26.31 (T3: 32.15). In addition, the majority of the method factor loadings are insignificant. The maximum loading of one indicator was T0: .170 (T3: .228); however, this was assigned to a different substantive factor with T0: .857 (T3: .838). We concluded that common method bias was absent or negligibly low.

Descriptives

Descriptive statistics of all variables in the structural equation model are compiled in Table 1.

Model variables			**Inter-construct correlations**					
	M	**SD**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(1) EDPI behaviour_Before the crisis (T0)	3.22	1.04		$.76^{***}$	$.74^{***}$	$.71^{***}$	$.33^{***}$	$.41^{***}$
(2) EDPI behaviour_Early within the crisis (T1)	3.02	0.98			$.74^{***}$	$.68^{***}$	$.20^{*}$	$.42^{***}$

(3) EDPI behaviour_7 months within the crisis (T2)	2.98	0.93				.66***	.28**	.40***
(4) EDPI behaviour_One year within the crisis (T3)	3.09	1.04					.30**	.51***
(5) Mental model regarding process digitalisation (T0)	3.82	0.70						.52***
(6) Mental model regarding process digitalisation (T3)	3.68	0.81						

Table 1. Descriptive statistics and correlations among variables
(Notes: N=130, M=Mean, SD=Standard Deviation; * $p < .05$; ** $p < .01$; *** $p < .001$; two-tailed tests)

Test of Hypotheses

In the following, the results from testing the hypotheses with a PLS-model are presented (Figure 3).[2] Hypothesis 1.1, stating that the mental model regarding process digitalisation is positively related to EDPI behaviour before the crisis (T0), is supported (β = .230, $p < .05$). Hypothesis 1.2, stating that the mental model regarding process digitalisation is positively related to EDPI behaviour early within the crisis (T1), is not supported (β = -.040, p = .336). Hypothesis 1.3, stating that the mental model regarding process digitalisation is positively related to EDPI behaviour 7 months within the crisis (T2), is not supported (β = .053, p = .276). Hypothesis 1.4, stating that the mental model regarding process digitalisation is positively related to EDPI behaviour one year within the crisis (T3), is supported (β = .197, $p < .05$).

As the results differ significantly for the different points in time, the empirical evidence supports hypothesis 2 that the relationship between mental models regarding process digitalisation and EDPI behaviour is changing over the time of a crisis. Conducting a RMANOVA of EDPI behaviour with the four points in time (T0-T3) in an isolated analysis, shows significant results for the overall sample in a linear decreasing path (F(1) = 4,029, $p < .05$) as well as in a quadratic manner (F(1) = 10.800, $p < .001$). It is important to note that actual working time during a crisis, relative working time in homeoffice, and physical presence at the workplace (T1-T3) as well as the expected company development in T3 did not influence this result. It has also to be noted that the mental model values measured in T0 and T3 significantly decreased by 3.8% which was tested with a paired t-test (T(129) = 2.135, $p < .05$.[3] We also separated the participants in quartiles regarding their mental model values for T0 and T3 independently and found, however, that the assignment to quartiles was robust across measurement points according to a Chi2-test (Chi2(9) = 46.293, $p < .001$).

Furthermore, we conducted a post-hoc analysis regarding hypothesis 2 to better understand the effects of the ongoing crisis on the relationship between mental models regarding process digitalisation and EDPI behaviour in which we examined data from participants with the 25% lowest (1 to 3.5) and 25% highest (4.29 to 5) mental model values (using the T0 values). Figure 4 shows the descriptives on how their EDPI behaviour changed before and within the crisis.

Conducting a RMANOVA among the 25% of employees with the lowest mental model values shows no linear significant effect over time (F(1) = 2.304, p = .139) as well as no quadratic effect (F(1) = 1.223, p = .277). In contrast, there is a significant quadratic effect during the crisis among the 25% of employees with the highest mental model values (F(1) = 12.029, p = .002). More specifically, in this group of employees, we observed a drop of EDPI behaviour of 11.8% between T0 and T1 which is almost remaining stable at T2 while the difference between T0 and T3 shows a recovery, i.e., only a decrease of 4.7%. Hence, there is support for H2 regarding the group of 25% employees with the highest mental model values, but not for the 25% lowest group of mental model values, which represents an unexpected, yet, interesting result.

[2] A robustness check without the influence of prior mental models and prior EDPI behavior reveals an R^2 of .23 for EDPI T1, .20 for EDPI T2 and .39 for EDPI in T3. Removing these influences does not change the results.
[3] Testing the structural model with mental models regarding process digitalization using the variable from T0 only, does not change the results of the model (Results see Appendix A-2).

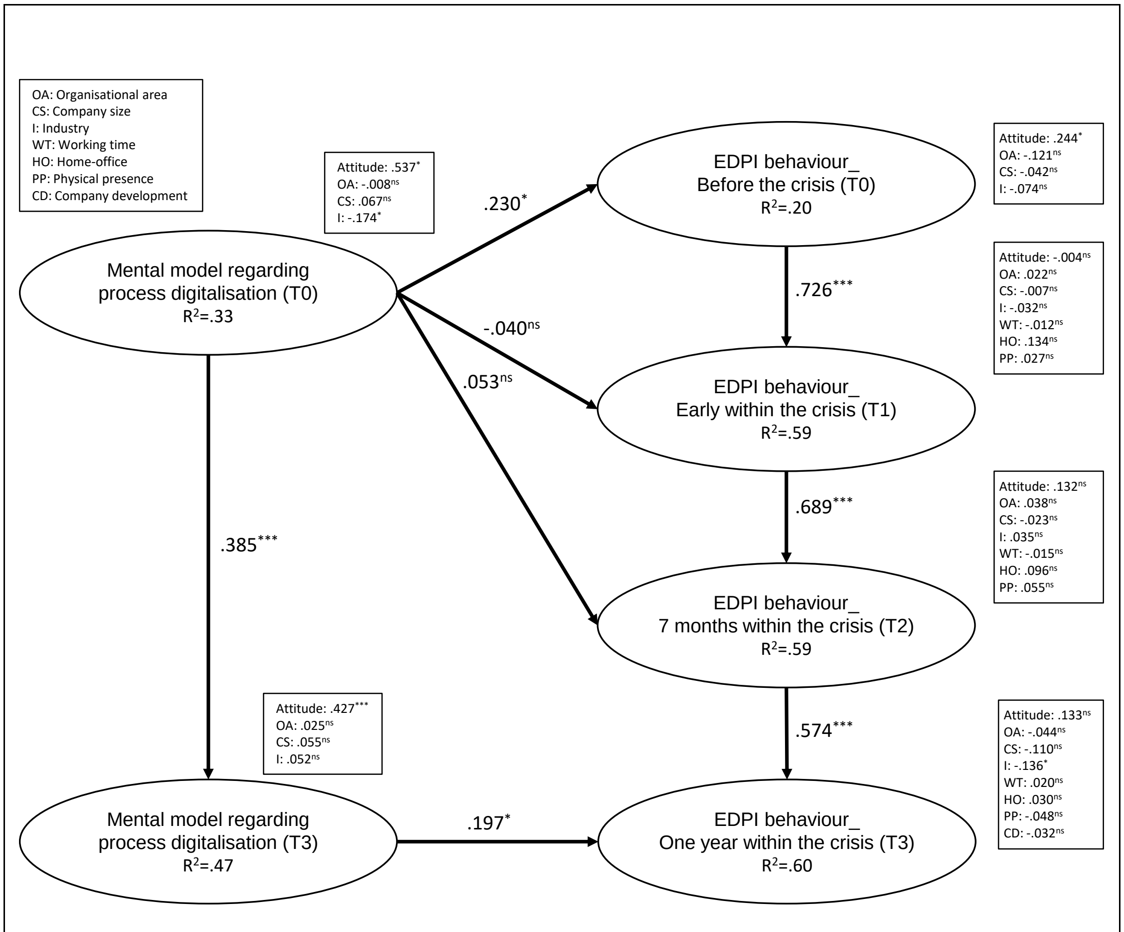

Figure 3. Results (* p < .05; ** p < .01; *** p < .001; one-tailed tests, n = 130)

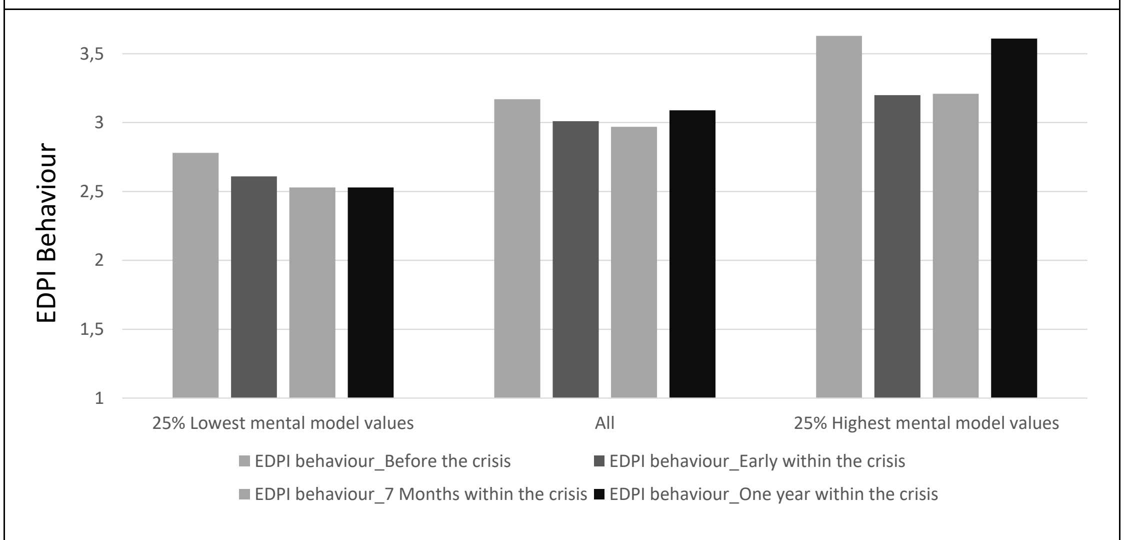

Figure 4. Results of the post-hoc analysis

Discussion

Addressing the research question of how employees' mental models influence EDPI behaviour during a crisis compared to 'normal' times, we contribute explanatory knowledge to two relevant research streams in the IS context: First, our findings contribute a quantitative-empirical evolution perspective during times of a crisis to the newly emerging field of EDPI (Høyrup 2010; Kesting et al. 2016; Opland et al. 2020; Opland et al. 2022), which, so far, lacks quantitative studies (Opland et al. 2020) and insights on the preconditions of employee-driven digital innovation (Opland et al. 2022). Second, we shed light on the cognitive drivers of individual innovation behaviour (Ramamoorthy et al. 2005; Wu et al. 2014), specifically investigating the influence of mental models (as dispositional antecedents) on EDPI behaviour during a crisis compared to 'normal' times. Thereby, we complement existing research on the role of cognitive antecedents of individual behaviour in the IS domain (e.g. Barkhi 2002; Lin and Chang 2018), that has, so far, hardly recognized mental models as relevant drivers of digital innovation behaviour.

As expected from theory, we found that mental models have a significant influence on EDPI in 'normal' times. This is in line with previous research which showed that mental models have a similar impact on other individual behaviour such as decision making (Davis and Yi 2004; Gary and Wood 2011; Ritchie-Dunham et al. 2007). Unexpectedly, over the course of the Corona crisis that began in early 2020 and started to have an impact in Germany from March 2020 on, we have found this relationship losing robustness. Whereas employees with less accurate mental models continued their EDPI behaviour on an unchanged and comparably low level, employees with more accurate mental models suddenly engaged significantly less during the first COVID 19 lockdown (i.e., early within the crisis when it was most acute). Over the remaining crisis periods, these employees with more accurate mental models then slowly regained their higher EDPI behaviour showing a quadratic relationship over time (see Figure 4).

Potential generalized explanations for these different effects of the crisis on the EDPI behaviour of employees with more and less accurate mental models can be related to the mental models "explanatory power for understanding" (Norman 1983, p. 7). Employees with well-developed mental models can better understand their individual innovation behaviour's expected impact, which is supposedly limited and uncertain in crisis times in terms of future work conditions as well as length and economic consequences of the lockdown (Kiss and Österholm 2020). Put differently, employees with well-developed mental models might have a better understanding in terms of their EDPI behaviour's impact, which might be limited in the crisis from their point of view. As a result, the effectiveness of EDPI behaviour might have been uncertain, and employees with more accurate mental models may have felt less inclined to engage and thus are less robust in showing EDPI behaviour. This finding, however, also points to less trust of employees (compared to 'normal' times) in that their EDPI behaviour leads to impact in the organisation's digital transformation process in general. Support for this interpretation can be found by the increase of EDPI behaviour of this group of employees back to normal one year within the crisis. This interpretation is further qualitatively supported by comments of the survey respondents (as contributed in the open box for commentaries at the end of the questionnaire), where one employee stated that his "employer first had to find out for himself on the basis of a pandemic that modern technology brings improvements in everyday life". Since major economic indicators have shown positive trends also reflected in higher export numbers and stock market prices and vaccination plans were executed after one year within the crisis, employees were back to seeing an end to the situation and potential positive impact of their EDPI behaviour. Thus, their EDPI behaviour has come almost back to 'normal', i.e., as before the crisis.

Employees having less accurate mental models have engaged to a similar degree in EDPI during the crisis as compared to before, potentially, because their EDPI behaviour's impact was less understood and questioned. Moreover, the results indicate that the respondents have seen more sense in doing so, not because they fully understood the potential impact of their activities, but because they aimed at demonstrating their EDPI behaviour to management driven by fear of being among the first to suffer negative consequences in these uncertain times. Along these lines, some respondents were indeed stating that "digitalisation will shape and dominate the corporate world (even more) in the future. Those who do not go along with the change are left behind.", "I feel compelled to do so in order not to be left behind." and that EDPI behavior will help to "securing my job also in the future.".

Conclusion

Digital innovation driving digital transformations has become critical for any organisation – even more so during times of a crisis such as the COVI 19 pandemic, as digital tools have gained importance. It is, therefore, essential that we develop an understanding of antecedents influencing EDPI at the individual level. We believe that this study is theoretically and practically relevant, and that it provides fellow researchers with a foundation to continue research on EDPI in 'normal' times and times of a crisis.

Theoretical Implications

Contributing to the topic of employee-driven innovation (Høyrup 2010; Kesting et al. 2016; Opland et al. 2020; Opland et al. 2022) and cognitive antecedents of individual innovation behaviour (Ramamoorthy et al. 2005; Wu et al. 2014), our study entails three major theoretical implications: First, we provide evidence of the influence that mental models have on EDPI. Specifically, our research yields novel insights concerning the diverging effects of mental models on EDPI behaviour in non-crisis versus crisis times. The results imply that the relationship between mental models and EDPI behaviour is positively related, but the higher the mental model's accuracy the less stable is the relationship during crisis times. Hence, we provide insights not only on the direction of the relationship, but also on the strength. It has to be considered that although it is preferable to achieve higher levels of accuracy of employees' mental models in general, our research shows that the investment into employees' mental models also increases the fragility of the EDPI outcomes during a crisis such as the COVID 19 pandemic. This finding, that lower robustness is a trade-off for mental models' "explanatory power for understanding" (Norman 1983, p. 7), should be considered when analysing similar constructs (e.g., work engagement, operational performance).

Second, our work has theoretical implications for IS research at the crossroads between digital innovation and digital transformation (Drechsler et al. 2020; Vial 2019) by providing insights into the mechanisms of mental models as antecedents influencing EDPI behaviour. Thereby, we provide and rely on unique longitudinal data during the COVID 19 pandemic that facilitates a better understanding of the relationship between mental models and EDPI behaviour and how it is different during times of a crisis and 'normal' times. It is especially noteworthy that employees with more accurate mental models decrease their EDPI behaviour in crisis times which is, however, critical for the competitiveness in crisis times in particular and the digital transformation of companies in general. Companies that drive innovation especially in times of a crisis are more likely to succeed in the long-term, especially when the crisis is over (Bar Am et al. 2020). Thus, EDPI behaviour from employees with more accurate mental models is crucial and has to be supported, especially during crisis times. Future research should therefore examine how to best address and engage employees with more accurate mental models, so they can view the crisis as an opportunity to accelerate innovation (Gkeredakis et al. 2021) and, thus, to keep their high level of EDPI behaviour.

Third, our results highlight the importance of analysing and further investigating the effects of exogenous shocks – such as the COVID 19 pandemic – on the digital innovation behaviour of individual employees affecting organisations' digital transformation efforts. Due to the timeliness of the Corona crisis, our knowledge on digital innovation during the COVID 19 pandemic in the context of IS is still limited (e.g. Buck forthcoming; Fletcher and Griffiths 2020). To the best of our knowledge, our study is the first to examine and compare the diverging influence of mental models on EDPI behaviour during times of a crisis based on rich longitudinal data, where individual and organisational innovation plays an even greater role in paving the way for (digital) transformation success and growth in the aftermath (Bar Am et al. 2020).

Managerial Implications

Our research makes a significant contribution to practice. Digital technologies enable ordinary, operational employees to contribute to innovative (digital) practices in their work context driving digital transformations. However, it remains unclear how organisations can effectively stimulate such EDPI (Bäckström and Bengtsson 2019; Opland et al. 2020). Thus, our study provides managers with valuable insights on the cognitive antecedents driving their employees' EDPI behaviour in 'normal' times and times of a crisis.

In non-crisis times, managers should approach their employees' mental models as significant drivers of EDPI behaviour. As a consequence, managers wishing to leverage their employees' innovation potential should invest in mental model building, e.g., by offering training to enhance their understanding of relevant system relations knowledge, by fostering structured dialogues among employees, or by identifying employees who need more focused support to develop their mental models regarding process digitalisation. Further, managers should endeavour to signal that EDPI activities are supported and welcome to increase understanding among employees and translating mental models into EDPI behaviour. More specifically, our research implies an increasing relevance of the analysis and design of information systems in general and user interfaces in particular. Managers are asked to challenge and improve the design of the current and future information systems and user interfaces their operational employees are confronted with aiming to support their imagination of the work processes and corresponding innovation potential. For example, process mining techniques might support the visualization of work processes (Martin et al. 2021; van der Aalst et al. 2012) and, thus, the building of accurate mental models regarding process digitalization.

In times of a crisis, our work yields different insights for managers with regards to EDPI. In this case, managers should account for further influencing factors and, in particular, acknowledge that employees with more accurate mental models might reduce their EDPI behaviour due to a lack of understanding their behaviour's relevant impact during the crisis. Whereas in non-crisis times, managers' focus should be on supporting operational employees with less accurate mental models to improve their mental models' accuracy, in times of a crisis, managers should instead focus on employees with more accurate mental models. For these employees, maintaining a high level of understanding and explanatory power will be of crucial importance for continued EDPI behaviour – at least in the case of operational employees as targeted in this study. To support this, managers should signal their certainty and purpose (Rigotti et al. 2020) that engaging in EDPI has a positive impact – even in uncertain times – for innovation and become even more important for success after a crisis (Bar Am et al. 2020). This is in line with research by Bartsch et al. (2020) who emphasized the role of leadership in times of a crisis to support digital transformation.

Limitations and Future Work

As with any research, our work is subject to limitations. First, our empirical study focused on EDPI behaviour on an individual level of analysis, although other studies have demonstrated that collaboration among employees is relevant to innovation efforts (e.g. Tarafdar and Gordon 2007). Since, employees act individually but are part of an organization, employee-driven digital innovation activities are most of the times dependent on others. Hence, the level of the individual behaviour is partly mixed with a group and organizational level. While the focus on individual behaviour has the advantage to unfold the individual reasoning especially with the focus on mental models, group and organizational influences on the individual level are also existing but require different theoretical explanations. There can be three perspectives of considering relevant theory-based influences. First, the individual mental model understanding can be extended to study the effect of shared mental models within groups (Leyer et al. 2022). Second, group effects relating to colleagues in different functions and similar processes working together should be incorporated with more details referring to social interaction theories and their effects on the possibilities of individual behaviour. Third, the organizational perspective should be considered referring to the role of employee-driven behaviour in the context of dynamic capabilities.

Second, it should be noted that we surveyed German employees who occupy operational roles in medium-sized to large companies, i.e., persons not involved in leadership or academic research or lecturing. In the future, the role of mental models and their drivers should be examined with regards to a broader (international) sample of operational employees. It may also be interesting to study cognitive factors influencing digital innovation behaviour in other roles such as leadership positions. Future research on the transferability of our results to other roles would be particularly interesting in the academic context, where digital process innovation was obviously and successfully accelerated by the Corona crisis (e.g., in the form of online lectures). In both cases, cultural effects are expected to lead to different results as cultural dimensions (e.g., power distance) differ between countries (Hofstede et al. 2010).

Third, although we believe that our study's results can be generalized to a broader crisis context, our underlying empirical insights draw from a health-related crisis that was driven by a virus. While certain factors relating of missing experience and uncertainty regarding the situation are similar to other types of crises (e.g., natural disasters, economic crises), other factors such as being isolated at home and the change in digital work environments are unique. Next crises might not be health-related. Instead, we can already see potential crises related to energy provision, inflation, extreme weather and military conflicts on the horizon. Hence, it may be promising to examine the transferability of our findings to other types of crises.

Fourth, the sample size is relatively small to draw generalizable conclusions for theory. While at the time of the first data gathering the extent of the crisis was not foreseeable, we checked for data gathering whether drop-outs occurred implying a systematic bias. Future work should always be aware of the mentioned crisis and consider higher number of observations than usual to prepare comparable long-term studies.

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Appendix

A-1. Measurement model

Construct		**ID**	**Item**
Employee-driven digital process innovation	Idea generation	IGE_1	I have ideas for the digital innovation of activities in my area of operations.
		IGE_2	I participate in the development of new digital ideas for activities in my area of operations.
		IGE_3	I participate in the identification of innovative digital solutions to problems.
	Idea cha mpi-	ICH_1	I participate in creating a vision of digital progression for my area of operations.
		ICH_2	I try to persuade colleagues to support innovative digital ideas.

		ICH_3	I make important organizational members in my area of operations enthusiastic about innovative digital ideas.
	Idea implementation	IIM_1	I am often the first in our team to try to implement new digital ideas in our area of operations.
		IIM_2	I participate in the implementation of new digital ideas.
		IIM_3	I systematically introduce innovative digital ideas into work practices.
Mental model regarding process digitalisation (Following ideas of Davenport (1993))		MM_1	I can imagine how activities in my area of operations will change due to the introduction of new digital solutions.
		MM_2	I can imagine how my activities to deliver results for external customers will change due to the introduction of new digital solutions.
		MM_3	I can imagine how collaborations with colleagues involved in delivering joint results for external customers will change due to the introduction of new digital solutions.
		MM_4	I can imagine how the requirements of external customers might be better fulfilled due to the introduction of new digital solutions.
		MM_5	I can imagine how the software I am currently using will be changed due to the introduction of new digital solutions.
		MM_6	I can imagine how collaboration with external partners will change due to the introduction of new digital solutions.
Controls (Fishbein and Ajzen (2010))	Attitude	A_1	Digital process innovation is beneficiary.
		A_2	Digital process innovation is important.
		A_3	Digital process innovation is gratifying.
		A_4	Digital process innovation is necessary.
	Organisational area (OA)		Please indicate your organisational area: Operations/production, Audit/Quality mgmt., Procurement, Finance/Accounting, IT, Customer service, Logistics, Marketing, HR, Process engineering, Product development/R&D, Product mgmt., Project mgmt., Strategy, Sales
	Company size (CS)		Please indicate the size of the company you are working for
	Industry (I)		Please indicate in which industry the company you are working for is operating: Engineering, Car manufacturer/OEM, Finance, Chemical, Electronics, Energy supply, Healthcare, Trading, IT/Telecommunication, Consumer goods, Metal eng., Public institutions, Pharmaceutical, Logistics
	Actual working time (AWT)		Please indicate the percentage of your working time in the last 6 weeks compared to your normal working hours: 0%, 20%, 40%, 60%, 80%, 100%
	Homeoffice time (HT)		Please indicate how much of your working time you have worked from home: 0%, 20%, 40%, 60%, 80%, 100%
	On-site working time (OWT)		Please indicate how much of your working time you were present on your employer's premises: 0%, 20%, 40%, 60%, 80%, 100%
	Company development (CD)		Please indicate what your opinion on the economic development of the company you are working in is in this year: Negative development, No substantial changes, Positive development