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Do digital competencies and social support boost work engagement during the COVID-19 pandemic?

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ABSTRACT

In today's world of work, the need for digital communication and collaboration competencies became even more prevalent during the ongoing COVID-19 pandemic. Yet, research and practice are lacking solid measurement instruments assessing digital communication and collaboration competencies of workers so far. Furthermore, it is yet unknown if digital communication and collaboration competencies and other so far known resources indeed act as drivers of work engagement during the pandemic. Based on the Job Demands-Resources (JD-R) model and the conservation of resources theory, we hypothesized that personal (digital communication and collaboration competencies) and job (social support) resources positively influence each other over time, also boosting work engagement. In a cross-lagged study design during the pandemic, we investigated our hypotheses in a sample of German workers ($N = 231$). Against our expectations, we did not find support for effects from personal or job resources on work engagement over time or effects of the resources influencing each other. Instead, we found high stabilities of digital communication and collaboration competencies and work engagement. Our results provide important insights into the motivational process of individuals working during a pandemic. The theoretical and practical implications for the JD-R model in times of crisis are discussed.

Technological innovations and the endeavour to maximize the efficiency of workflows result in fast and constantly changing workplaces for most workers (e.g., DeShon & Gillespie, 2005). Consequently, the need to use digital information and communication technology (ICT) to accomplish work tasks gained pace rapidly. Already in 2016, 83% of the participants in a large representative German workforce sample confirmed to use digital ICT daily (Arnold et al., 2016). As job tasks become more complex in such an increasingly global and technology-based work environment, people have to communicate and collaborate online to solve crucial problems using interactive work forms (DeShon & Gillespie, 2005; Gilson et al., 2014). Therefore, especially digital communication and collaboration competencies are essential assets needed to get work done efficiently, which is why we concentrated on these two digital competencies in this current research. The importance of such competencies became even more prevalent during the COVID-19 pandemic (Wang et al., 2021) since social distancing is required as an important measure to fight the worldwide crisis. Overnight, face-to-face meetings are not happening anymore and all communication and collaboration at work shifted online. Yet, research and practice are lacking solid measurement instruments assessing these important digital competencies of workers so far (e.g., Murawski & Bick, 2017).

Therefore, the first aim of our current research was to develop a questionnaire measuring digital communication and collaboration competencies at work, using two samples of German workers. By this, we aimed to enable organizations and workers themselves to assess and evaluate the status of these important competencies in the workforce. Second, we investigated the potential role of digital communication and collaboration competencies as a personal resource in times of crisis in the motivational process outlined by the Job Demands-Resources (JD-R, Demerouti et al., 2001) model in a cross-lagged study design during COVID-19. Besides personal resources, the job resource social support gained importance during the COVID-19 crisis that requires workers to social distance and work remotely (Wang et al., 2021). This leads to our third aim, which was to examine if personal (digital communication and collaboration competencies) and job (social support) resources have positive reciprocal effects over time when faced with the specific demands of working under COVID-19 conditions, ultimately boosting work engagement. Finally, we tested for positive reciprocal effects between personal and job resources and work engagement over time

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during the COVID-19 pandemic. Thereby, our research offers important insights into the motivational effects of personal and job resources on work engagement in times of crisis.

1. Digital communication and collaboration competencies at work

In line with prior definitions, we understand digital competencies as a combination of knowledge, skills, abilities, and other characteristics, such as motivational aspects (Aamodt, 2009). Digital competencies encompass a range of different competencies, which are central in the accomplishment of regular job tasks involving digital media, such as the handling of hardware, analysing and evaluating data, or networking online. Building on a comprehensive model of digital competencies that has been suggested recently (Oberländer et al., 2020), we concentrated on digital communication competencies on the one hand and digital collaboration competencies on the other hand.

In detail, digital communication competencies are defined as "the competency to use appropriate digital communication channels to communicate with colleagues, supervisors and business partners" (Oberländer et al., 2020, in the supplementary material, SM, p. 3). This includes knowing all of the digital communication channels that are used frequently in the organization or chatting with colleagues or writing e-mails in appropriate form and language in the work context, for example. Workers with high digital communication competencies can choose the best medium for (digital) communication and bring across their messages adequately.

Digital collaboration competencies are defined as "the competency to use digital media and programmes for business collaboration, for example with colleagues, supervisors, business partners, and customers" (Oberländer et al., 2020, SM, p. 3). This could require the use of shared team calendars, accessing work results of team members, or simultaneously working on the same documents or data with colleagues. Digital collaboration competencies enable professionals working in a wide range of industries and having different tasks and jobs to interact with others and distribute work between people regardless of their location (Schulze & Krumm, 2016). Workers with high digital collaboration competencies can access and share relevant information with team members quickly, for example by choosing the medium supporting the needs best.

Digital communication and collaboration are central competencies at work, both in theory and practice. First, these two competencies are not just included in most theoretical models about digital competencies but often take a prominent role within such models (e.g., Hertel et al., 2006; Hwang, 2011). However, empirical studies that contribute to the understanding of the nature of digital competencies and effects in the work context are still largely lacking (e.g., van Laar et al., 2019), even though there is a pressing need for the use and understanding of digital competencies at the workplace (e.g., Raghuram et al., 2019).

Second, in the modern world of work for organizations, both, digital communication and collaboration competencies are important assets in practice as they are inevitable in most office-based jobs to complete even basic job tasks. Therefore, digital communication and collaboration competencies are mentioned as core competencies in the twenty-first century frequently (Makarius & Larson, 2017; Schulze et al., 2017). Organizations rely on the digital competencies of their employees to improve the quality, effectiveness, and efficiency of their work (Derks et al., 2008). Indeed, successful communication has been linked positively to important and desirable organizational outcomes, such as performance (Hertel et al., 2006; Schulze & Krumm, 2016), interpersonal relations (Degbey & Einola, 2019; Hwang, 2011), or motivation (Lee et al., 2015).

Even though many aspects of digital communication and collaboration are similar to face-to-face situations in which co-workers or supervisors are collaborating and communicating, it must be considered a different theoretical construct posing unique challenges to the workforce (Degbey & Einola, 2019; Schulze et al., 2017). Oftentimes, digital communication is described as more challenging to workers than face-to-face interactions (Raghuram et al., 2019). Most obviously, any digital conversation or collaboration requires a basic understanding of the technology used, even though these competencies are not part of most official job training (Schulze et al., 2017). Expressing emotions, resolving conflicts, or building relations with colleagues or supervisors gets more difficult online, especially in asynchronous forms of communication, like texting (Ayoko et al., 2012; Liao, 2017).

1.1. Digital communication and collaboration competencies in times of COVID-19

The urgent need for digital communication and collaboration competencies became even more prevalent under the very recent changes in the world of work due to the global COVID-19 pandemic that caused nationwide lockdowns which abruptly forced the vast majority of workers to work from home (Imöhl & Ivanov, 2021; Wang et al., 2021). These governmental measures caused temporal halts in production, short-time work in many industries, the closure of nurseries and daycares for children, and supply shortages of important goods among others. Workers had to adjust to the new pandemic situation rapidly and manage childcare and working from home without a chance to establish thought-out concepts for digital collaboration (Weigelt et al., 2021).

Digital communication and collaboration replaced almost all in-person work settings wherever possible to comply with the social distancing rules that were in place in many countries (Meske & Junglas, 2020). Research from earlier epidemics indicates that communicating is an essential resource reducing strain (Chan & Huak, 2004; Matsuishi et al., 2012). With regard to work motivation, social support as an important, well-researched job resource (e.g., Nasurdin et al., 2018; Xanthopoulou et al., 2008), especially in times of crisis, was probably only easy to access for those with sufficient digital communication and collaboration competencies, as in-person meetings were not possible. Indeed, successful digital communication has been identified as a key challenge of the workforce during COVID-19 (Dirani et al., 2020; Wang et al., 2021). Against this background, we set out to develop a measurement instrument for individual digital communication and collaboration competencies at work. Furthermore, we tested the suggested central role of such competencies during the COVID-19 pandemic for employees and investigated their effect within a well-validated model of work motivation.

1.2. Resources at work and work engagement

The JD-R model (Demerouti et al., 2001) is used to explain the positive effects of job resources on desirable organizational outcomes, such as motivation, well-being, and performance. In the motivational process of the JD-R model, it is assumed that job (e.g. social support) or personal (e.g. emotional competences) resources trigger motivational processes at work by satisfying basic human needs (Bakker et al., 2007; Lorente Prieto et al., 2008; Xanthopoulou et al., 2009). In the frame of the JD-R model, motivation as a desirable work-related state is often represented by the construct of work engagement (Bakker et al., 2007; Mauno et al., 2007). Work engagement is defined as a fulfilling, affective, and work-related state of mind, characterized by its three facets vigor, dedication, and absorption (Xanthopoulou et al., 2009). In previous studies, work engagement has been positively associated with desirable work outcomes on the individual and organizational level, such as financial outcomes for organizations or customer satisfaction (Schneider et al., 2018). The positive impact of job resources on work engagement has been widely acknowledged (Bakker et al., 2007). For instance, Schaufeli et al. (2009) found that increases in job resources such as social support, autonomy, learning opportunities, and feedback predict work engagement. Especially under highly demanding circumstances, job resources foster work engagement (Bakker et al., 2007). As

the COVID-19 pandemic is an unprecedented global crisis, it changed the work situation fundamentally. Thus, workers need resources to handle this extraordinarily demanding situation.

As the JD-R model is rather open and heuristic, the (job and personal) resources are not restricted to specific constructs (Schaufeli & Taris, 2014). Demerouti et al. (2001) defined job resources as physical, social, organizational, and psychological aspects of the job that mitigate negative effects of job demands, are beneficial to achieve goals at work, and foster personal learning and development. More recently personal resources were included as part of an extended JD-R model (Schaufeli & Taris, 2014). Personal resources are those characteristics that individuals bring into the work situation that function as coping mechanisms, or foster work-related well-being. This is supported by findings of various personal resources boosting work engagement, such as stable characteristics in terms of core self-evaluations (Bipp et al., 2019), or optimism (Xanthopoulou et al., 2012). More importantly, the competencies of teachers have been shown to significantly predict work engagement over time in a way that more emotional competencies led to higher vigor and dedication (Lorente Prieto et al., 2008). Based on the outlined relevance of digital competencies at work, and in line with these prior findings, we expected that digital communication and collaboration competencies function as personal resources, boosting work engagement during the pandemic. Thereby, we assume that digital communication and collaboration competencies fulfil the basic human need for competence and foster intrinsic motivation at work (Bakker & Demerouti, 2008).

H1. *Digital (a) communication and (b) collaboration competencies each have positive lagged effects on work engagement.*

Besides investigating the role of communication and collaboration competencies as resources, we looked at the potential prominent role of another resource in times of crisis – social support. This job resource has been linked successfully in numerous, prior studies to increases in work engagement in the frame of the motivational process of the JD-R model (e.g., Bakker et al., 2004; de Jonge & Dormann, 2006). Social support at work includes support from supervisors and co-workers. For example, Xanthopoulou et al. (2008) surveyed flight attendants and showed the unique positive effects that colleague support had on work engagement. In addition to the established research on social support boosting work engagement, very recent research highlights the important role of social support during the ongoing pandemic. For example, social support was found to play a central role as a positive job resource, helping to cope with the demands during the crisis among healthcare professionals (Britt et al., 2020; Kisely et al., 2020). Moreover, Wang et al. (2021) conducted interviews with Chinese workers that were forced to work from home without any preparation or consent in advance due to governmental social distancing measures after the outbreak of COVID-19 in Wuhan. They noted that social support is not only a "necessary job resource to accomplish tasks" (p. 30) but also the "most powerful virtual work characteristic" while working from home during this special situation (Wang et al., 2021, p. 46). On the flip side, Wang et al. (2021) found workers feeling socially isolated during the COVID-19 outbreak to be a major challenge. In line with the JD-R model and prior findings, we argue that social support boosts work engagement, also during times of crisis.

H2. *Social support at work has a positive lagged effect on work engagement.*

According to the conservation of resources theory (COR, Hobfoll, 2011), people deeply aim to obtain and sustain the resources they value. The theory also proposes that those who possess more resources can gain further resources and protect them more easily. Thus, various resources foster each other in a reciprocal dynamic interplay over time, tend to accumulate, and ultimately lead to work engagement (Bakker & Demerouti, 2008; Hakanen et al., 2008). For instance, Simbula et al. (2011) observed reciprocal effects between job (social support) and personal (self-efficacy) resources and work engagement among schoolteachers in a longitudinal study. Moreover, Llorens et al. (2007) showed reciprocal effects between task resources, efficacy beliefs, and engagement in university students. However, to our knowledge, no study has shown if such reciprocal effects between resources and work engagement also show throughout the crisis. Such an effect can indeed be anticipated, as it is known that job resources become particularly salient when job demands are high (Bakker & Demerouti, 2008). Dirani et al. (2020) argue that communication and supporting workers are both among the most important competencies of leaders during times of crisis. However, it is yet unknown, if they really stimulate work engagement during a crisis and how they affect each other. Moreover, Britt et al. (2020) argue that personal resources are less examined within pandemics than job resources and if so, job and personal resources are investigated separately. By investigating the interrelationship between personal and job resources, we shed light on their interplay in times of crisis. In line with the theoretical reasoning, we expected that the job resource social support, and the personal resources digital communication and collaboration competencies affect each other positively over time during the COVID-19 pandemic.

H3. *Digital (a) communication and (b) collaboration competencies each have positive lagged effects on social support.*

H4. *Social support has positive lagged effects on digital (a) communication and (b) collaboration competencies.*

In addition to direct links from resources on motivation, our research model (Fig. 1) also posits that a high engagement in workers can positively influence the building of new resources. Empirical studies conducted before the pandemic suggest such reversed lagged effects of work engagement on job and personal resources (e.g., Bakker & Demerouti, 2008). The findings indicate that work engagement facilitates the activation of resources and helps create new resources. For instance, Xanthopoulou et al. (2009) showed that work engagement is related to both job and personal resources (e.g. self-efficacy, feedback). Additionally, Hakanen et al. (2008) found positive reciprocal cross-lagged relationships between job resources, personal initiative, and work engagement. Thus, we predict that engaged workers are better able to protect their job and personal resources and build new ones, in times of crisis.

H5. *Work engagement has positive lagged effects on resources in terms of a) digital communication, b) collaboration competencies, and c) social support.*

2. Prestudy: Initial questionnaire development

To our knowledge, there is no reliable and valid measurement instrument for digital communication competencies (DCM) and digital collaboration competencies (DCL) at work, yet. To test our hypotheses in the main study, we first conducted a prestudy to develop such a questionnaire based on the knowledge, skills, abilities, and others (KSAO) framework (Aamodt, 2009; Krumm et al., 2012) and the definition and framework of digital competencies at work (Oberländer et al., 2020).

2.1. Method

The five general steps that we took to the development of a self-report questionnaire reflecting workers' perception of their DCM and DCL are shown in Figure A (in the supplementary material, SM). perception of their DCM and DCL are shown in Figure A (in the electronic supplementary material, ESM).

2.1.1. Initial item pool

In a first step, we formulated items that represent the main content of DCM and DCL at work. On the one hand, the items were theoretically based on extracts from the existing literature about the definition of digital competencies at work (e.g., Janssen et al., 2013; van Laar et al., 2017). On the other hand, they were supplemented with a practical view by incorporating the definitions of DCM and DCL at work obtained from

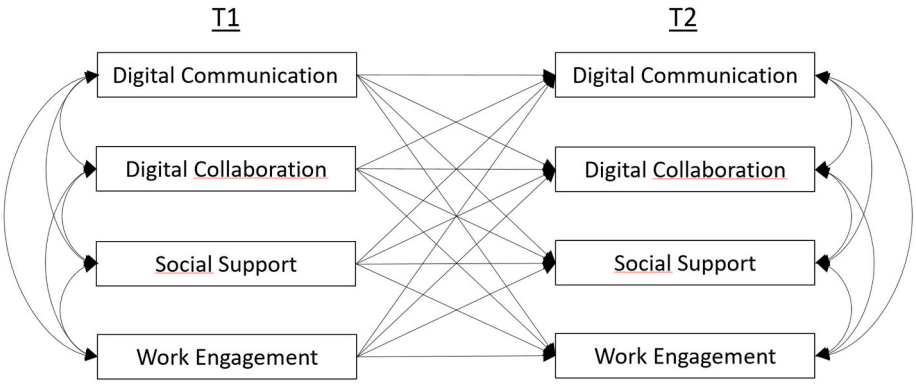

Fig. 1. Reciprocal model as research model.
Note. Theoretical model of latent variables to test reciprocal effects of resources and work engagement.

eleven interviews with practitioners. For the interviews, we focused on white-collar workers with office jobs using digital media frequently as a target group. Furthermore, we made an effort to formulate the items distinctively according to the KSAO framework, so that knowledge, skills/abilities, and other competencies were included. We drew particular attention to the wording of the items to avoid descriptions of job-specific tasks. This was due to the aim to use the items for white-collar workers in various jobs. Our efforts resulted in an initial formulation of 42 items.

2.1.2. Item revision

One of the authors of this study and a research assistant each rated the initial items on how close they were to the definitions of the respective competencies, and therefore the core of the constructs (following the recommendations of Clark & Watson, 1995). Another researcher with expertise in this area checked the wording of the items on clarity, transparency, redundancy, and conciseness and decided on the items with widely deviating ratings. This resulted in 19 items representing the facets of DCM (e.g. "*I know which type of digital communication I should use in different work-related situations.*") and eight items representing the facets of DCL (e.g. "*I can collaborate with others also online.*"). This initial pool of 27 items, including the original German items, and back- and forth-translated English wordings, is depicted in Table A (SM).

2.1.3. Measures and procedure

To pretest the items, we recruited various workers from private and professional networks to participate in an online survey in December 2019. After a general introduction and their agreement to participate voluntarily, we asked the participants to answer the 27 items on a 5-point-scale (1 *doesn't apply at all* to 5 *fully applies*), all presented in random order. Participants were asked to answer questions about their use of digital media at work and working hours, among other demographic questions.

2.1.4. Sample

The sample consisted of 89 women, 49 men, and one person with unspecified gender. The age of the participants ranged from 18 to 67 years with a mean age of 41.04 years ($SD = 12.82$). The mean of the self-reported average weekly working hours was 35.62 ($SD = 10.30$) and participants spent five to 100% of their working time with digital media ($M = 74.10$, $SD = 23.50$). Only one participant stated that neither a computer nor a laptop was available for them to do their work, in this case the only digital device was a smartphone. Just over half of the participants (50.3%) used smartphones at work. A majority of the participants (71.3%) had a degree from a university or college of higher education.

2.1.5. Analyses procedure

We evaluated the 27 items based on a combination of approaches from classical test theory (CTT) and item response theory (IRT). In detail, we analysed the items by looking at descriptive statistics based on CTT (e.g. mean values, standard deviations, item difficulties, kurtosis, skewness). Concurrently, we followed an IRT-based approach for the selection of the items using R and looked at the item information curves (IIC) and item response category characteristic curves (CCC) to assess if the item thresholds were sorted. The advantage of using IRT to complement the results of the CTT is the additional information that we get about every single item, which is overlooked by the methods of the CTT.

To test the factor structure of the questionnaire, we conducted an exploratory factor analysis (EFA) using IBM SPSS Statistics 25. Then, we conducted confirmatory factor analyses (CFA) using AMOS version 27.0.0 (Arbuckle, 2020) to validate the factor structure of the preliminary questionnaire. For this, we considered two different solutions: A one-factor model with all items as indicators for one latent variable, digital competencies, and a two-factor model with two latent variables, DCM and DCL. For all models, we used different goodness-of-fit indices to assess the fit of the data with the proposed model: The absolute goodness-of-fit indices χ^2, degrees of freedom, and Root Mean Square Error of Approximation (RMSEA). According to Browne and Cudeck (1993), RMSEA values below 0.05 indicate a very good fit and values smaller than 0.09 indicate an acceptable fit. Because the χ^2-statistic is sensitive to sample size, we additionally calculated the relative goodness-of-fit indices Normed Fit Index (NFI), Incremental Fit Index (IFI), and the Comparative Fit Index (CFI, Marsh et al., 1988). For the relative goodness-of-fit indices values greater than 0.90 indicate an acceptable fit (Hoyle, 1995).

2.2. Results and discussion

In a first step, we evaluated descriptive statistics of all 27 items based on CTT. The mean values for the CM and CL items were rather high in the sample, ranging between 3.21 and 4.47. Only for eighteen items, the whole rating scale was used by the participants. The distribution of responses for five items of the CM scale and two items of the CL scale was substantially skewed and the distribution of responses for eight items on the CM and one item on the CL scale were peaked. With regard to the IRT results, most of the items of the initial pool showed ordered thresholds, except six items on the CM and two items on the CL scale. For example, for item CM8 and CM15, the rating category 2 (*does rather not apply*) and for item CL2 the rating category 3 (*applies somewhat*) had lower probabilities than expected. In item CM12, the probability to choose the rating category 5 (*fully applies*) was very high for any ability. A look at the item information curves of the 27 items revealed that four items offered little information according to the item information curves. Three items offered to differentiate information in the higher part of the scale,

whereas seven items offered good information in the lower part of the scale.

Furthermore, we conducted an exploratory factor analysis (EFA) using maximum likelihood and an oblimin rotation with all of the 27 items (Hinkin, 1995). Horn's parallel analysis showed that two factors should be extracted, which fits the theoretical expectations. Two factors could explain 45% of the variance. All items from the CL scale showed substantial estimated loadings on factor 1 and most of the items from the CM scale showed substantial estimated loadings on factor 2. However, contrary to the expected structure, six items of the CM scale were loading higher on factor 1, and item CM1 showed substantial loadings on both factors. To further test the factor structure with CFAs, we contrasted a one-factor model (all items loading on a single factor) with a two-factor model (items of DCM and DCL loading on separate factors) for the initial 27 items. Table 1 displays the results. A chi-square difference test revealed a significantly better model fit for the two-factor solution ($\Delta\chi^2(1) = 1103.22$, $p < .001$). Nonetheless, fit indices indicated that there was still room for improvement in terms of model fit.

Taking all of this information based on CTT and IRT approaches into account and also considering the contextual overlap of some items, we decided to delete eleven items. This led to a reduced version of the questionnaire with 16 items (see items with * in Table A, SM). Consequently, we conducted two CFAs for the 16 items of the reduced questionnaire, contrasting a two-factor and a one-factor model. The best model fit was achieved with the two-factor model of the 16-item version ($\Delta\chi^2(1) = 180.97$, $p < .001$), which was also superior to the two-factor model with 27 items ($\Delta\chi^2(220) = 652.05$, $p < .001$). According to the standards, however, the indices were still unsatisfactory ($\chi^2/df = 2.33$, CFI = 0.87, RMSEA = 0.10).

In sum, based on the results of the prestudy and CTT and IRT approaches, we reduced the set of items from 27 to 16. Empirical investigation and analyses confirmed the theoretically anticipated two-factor structure, representing the two scales for DCM and DCL. Although we were able to develop a preliminary questionnaire to assess digital competencies at work, the overall results implied that there was still potential to optimize it. Therefore, we tested the obtained 16 items from the preliminary questionnaire at T1 of our main study with another sample. Additionally, to counteract the high mean values, we adapted the rating scale to a 7-point Likert scale in the following.

Table 1
Goodness-of-fit statistics of the digital communication and collaboration competencies scales for the prestudy and for the main study (T1 and T2).

Model	χ^2	df	$\Delta\chi^2(\Delta df)$	NFI	IFI	CFI	RMSEA
Prestudy ($N = 145$)							
One factor (27 items)	1995.27	324		.39	.43	.43	.19
Two factors (27 items)	892.05	323	1103.22 (1)	.73	.81	.81	.11
One factor (16 items)	420.97	104		.64	.70	.70	.15
Two factors (16 items)	240.00	103	180.97(1)	.80	.87	.87	.10
One factor (10 items)	106.35	35		.80	.86	.85	.12
Two factors (10 items)	55.12	34	51.23(1)	.90	.96	.96	.07
T1 ($N = 231$)							
One factor (16 items)	507.90	104		.62	.68	.67	.13
Two factors (16 items)	446.02	103	61.88(1)	.68	.73	.73	.12
One factor (10 items)	116.47	35		.79	.84	.84	.10
Two factors (10 items)	65.68	34	50.79(1)	.88	.94	.94	.07
T2 ($N = 170$)							
One factor (10 items)	190.01	36		.67	.71	.70	.13
Two factors (10 items)	73.43	34	116.58(1)	.87	.93	.92	.07

Note. χ^2 = chi-square fit index, *df* = degrees of freedom, NFI = Normed Fit Index; IFI = Incremental Fit Index; CFI = Comparative-Fit-Index; RMSEA = Root-Mean-Square-Error-of-Approximation; AIC = Akaike's An Information Criterion. Chi-square difference tests compare to the previous model. All tests are significant with $p < .001$.

3. Main study: The interplay of digital competencies, social support, and work engagement

In the main study, we cross-validated the scales for DCM and DCL with another sample of workers and improved it by further reduction of items. Furthermore, we tested our hypothesis about the role of DCM and DCL and social support at work as positive resources in the motivational process in times of crisis (H1-H5).

3.1. Method

3.1.1. Settings and participants

Data were collected from German workers in two waves with a minimum time lag of ten weeks. The first wave of data collection lasted from April 09th to June 14th, 2020, starting after the German government imposed drastic measures to condemn the COVID-19 pandemic and many companies established stay-at-home policies. The second wave of data collection took place from August 3rd to September 16th, 2020, when most measures were relaxed and many workers returned to the offices. Participants were recruited from different sources, including the extended private and professional network, social networks, and a press release of the University. The survey was implemented at the platform *Unipark*, where interested individuals could participate via a link. Participants were informed about the procedure of the survey and asked for consent. The only prerequisite for participation was a professional activity using digital media at least for some tasks at work. The participation was voluntary and unpaid, but participants were offered a handout with practical information about working from home based on scientific results and information about the results after completing the surveys.

During the first wave of data collection, 265 persons started to answer the questions. Of the 252 participants who finished the survey, 231 provided complete data at T1. The sample consisted of 147 persons identifying as female, 79 persons identifying as male, and five persons who did not specify their gender. The participants' ages range from 21 to 64 ($M = 38.04$, $SD = 11.71$). The mean tenure is 12.76 years ($Mdn = 8.00$, $SD = 11.72$) and the participants' mean weekly work time is 34.63 hours ($Mdn = 40.00$, $SD = 11.71$). A majority of the participants (71%) are working full-time. At T1, most of the participants (66.5%) stated that they work from home the whole time, some (23.3%) of the participants work from home temporarily and only ten percent of the participants do not work from home at all. All of the participants work with a computer and participants' self-reported time working with any kind of digital media makes between ten and 100 percent of their whole working time ($Mdn = 99.00$). Most participants work in the IT sector ($N = 40$), freelancing, scientific and technological services ($N = 32$), public administration ($N = 29$), education and teaching ($N = 25$), or healthcare and social services ($N = 23$).

We examined whether the participants who answered the survey at T2 ($N_{T2} = 175$) differed from the participants who dropped out ($N = 54$) to control for potential (self) selection bias. We used a MANOVA to check for differences in the study variables (digital communication, digital collaboration competencies, social support, work engagement) and demographic variables (prior working from home experience, working hours, working from home, working time spent with digital media). Results revealed that there was no sign for systematic dropout in our study, $F(11, 184) = 1.61$, $p = .10$.

3.1.2. Measures

Digital Communication and Collaboration Competencies. We used the preliminary 16-item-questionnaire developed in the prestudy to assess DCM and DCL. Given that the 16 items from the prestudy did not show satisfactory model fit indices, we evaluated again the scales with the data of the full sample from T1 ($N = 231$).

First, we looked at the descriptive psychometrics of the items based on CTT. The mean values for the 16 items on DCM and DCL ranged between 5.36 and 6.52. Only for six items, the full range of the rating scale (from 1 to 7) was used, while for five items the minimum rating category used by the participants was category 3 (*does rather not apply*). The distribution of responses was substantially skewed to the left for all items. Additionally, we considered IRT-based results using the data of T1. For three items, more than two thresholds were not ordered. The item information curves revealed that four items offered differentiated information, especially in the lower part of the scale.

Taking all of this information into account, we excluded six items from the further analysis (see Table A, SM). The final ten items (five items for each scale) were tested for their factor structure, using a CFA to test a two-factor model against a one-factor model. The two-factor model of the 10-item questionnaire showed a good fit with the data of the prestudy ($\chi^2/df = 1.62$, CFI = 0.96, RMSEA = 0.07) and T1 ($\chi^2/df = 1.93$, CFI = 0.94, RMSEA = 0.07) that was also superior to all of the other solutions (cf. Table 1). The internal consistency for DCM (Cronbach's $\alpha = 0.70$) and DCL (Cronbach's $\alpha = 0.77$) competencies indicated acceptable reliability of the two scales in the final version (Field, 2009; Kline, 1999). The correlation between the two latent factors in the model was $r_{T1} = 0.67$, $p < .001$, and $r_{prestudy} = .68$, $p < .001$.

Social Support. To measure social support at work, we used the 3-item scale from the well-established and validated German Short Work Analysis Questionnaire ("Kurzfragebogen zur Arbeitsanalyse", Prümper et al., 1995) assessing social support at work from others (e.g., colleagues, supervisor). A sample item is "I can rely on my colleagues when it gets difficult at work". The items were rated on a 5-point Likert scale (1 = *doesn't apply at all* to 5 = *fully applies*).

Work Engagement. Work engagement was measured with the German version of the three items of the validated short-version of the Utrecht Work Engagement Scale (UWES-3), which has been shown to be as reliable and valid as the 9-item version (Schaufeli et al., 2019). Each item represents one of the underlying dimensions vigor, dedication, and absorption (e.g., "I am enthusiastic about my job."). The items were rated on a 7-point Likert scale (1 = *never* to 7 = *always*).

3.1.3. Analytic strategy

To test our hypotheses, we fitted four different models to the data consecutively using structural equation modeling (SEM) techniques in AMOS version 27.0.0 (Arbuckle, 2020) with maximum likelihood. The first model (stability model) included paths of the study variables between T1 and T2 as well as correlations between the constructs measured at T1 and T2. Measurement errors of corresponding items of T1 and T2 were allowed to covary over time as their wording was identical (Llorens et al., 2007). In the following, we compare this stability model to three nested models to test our hypothesis about reciprocal effects and stability over time. The second model included all paths of the stability model and additionally the cross-lagged paths from the resources to work engagement as well as the paths from digital competencies to social support. In detail, we included paths from DCM and DCL T1, and social support T1 to work engagement T2, and from DCM and DCL T1 to social support T2 (causality model). The third model was identical to the stability model but included additional paths from social support T1 and work engagement T1 to DCM T2, DCL T2, and social support T2 (reversed causation model). The fourth model included all of the previously mentioned paths in one model (reciprocal model, cf. Fig. 1).

3.2. Results and discussion

Descriptive statistics for the study variables at T1 and T2 are depicted in Table 2. The internal consistencies were all satisfactory. The mean values for DCM and DCL and social support were high for T1 and T2. Differences in means between T1 and T2 were not significant for any study variables, except for social support that was significantly decreasing from T1 to T2, $t(162) = 3.24$, $p < .01$, Cohens $d = 0.53$. In general, the pattern of correlations shows that, as expected, all study variables are significantly positively related to each other at each measurement point (T1 and T2).

With regard to the fit indices of the tested models, the stability model is superior to all other models (Table 3). According to the recommendations, the fit indices indicate a very good fit of the stability model with the data. The autocorrelations between T1 and T2 are .83 for DCM, .72 for DCL, .80 for social support, and .87 for work engagement (cf. Fig. 2). All manifest variables loaded significantly on the intended latent factors. Covariances between study variables were all significant with $p < .01$, except for work engagement and DCL (T1), which were significant with $p = .03$, and social support and DCM (T2), which were not significant.

The causality model also displayed a very good fit with the data. However, none of the cross-lagged paths from resources to work engagement (H1, H2) and DCM or DCL to social support (H3) were significant. A chi-square difference test revealed no significant difference between the stability and the causality model ($\Delta\chi^2(5) = 4.08$, $p = .54$). Following the parsimony principle that suggests choosing more parsimonious models over models with more presumed paths, the stability model is superior (Vandekerckhove et al., 2015).

The fit indices also showed a very good fit of the reversed causation model to the data. Nevertheless, the expected cross-lagged paths from social support (T1) to DCM and DCL (T2) were not significant (H4). Additionally, none of the cross-lagged paths from work engagement (T1) to the resources (T2) were significant (H5). In sum, the reversed causation model was not significantly better than the stability model, a chi-square difference test revealed ($\Delta\chi^2(5) = 1.60$, $p = .90$).

The reciprocal model including all hypothesized paths at once also showed a very good fit to the data. However, again neither the cross-lagged paths from the resources (T1) to work engagement (T2, H1, H2), nor the cross-lagged paths from social support (T1) to the personal resources (T2, H4) or from work engagement (T1) to the resources (T2, H5) were significant. Again, a chi-square difference test revealed that the reciprocal model was not significantly better than the stability model ($\Delta\chi^2(12) = 8.22$, $p = .77$).

Contrary to our expectations, we could not find cross-lagged effects of job or personal resources on work engagement (H1, H2) in the current study. Unlike assumed, we did not find evidence for DCM and DCL having the role of personal resources boosting work engagement during the pandemic, neither did we find evidence for social support boosting work engagement in times of crisis. This is surprising, given that, at least for social support, a vast amount of research findings before the pandemic provided evidence for such an effect (e.g., Xanthopoulou et al., 2008). Moreover, we neither found significant cross-lagged effects from DCM or DCL on social support (H3) nor from social support on DCM or DCL (H4). Therefore, we found no evidence for reciprocal effects between personal and job resources in times of crisis. Furthermore, we found no support for reciprocal effects between work engagement and resources during times of crisis (H5). However, all study variables showed very high autoregressive effects over the two time points, with only social support showing a substantial decline over time. The stability model showed the best fit with the data and was superior to all other models. Therefore, against our hypotheses, the model including only temporal stabilities and synchronous correlations shows a better fit with the data than all other models including relationships between job and personal resources and work engagement over time.

Table 2
Mean values, standard deviations, internal consistencies, and intercorrelations of all study variables (T1 and T2).

	M	SD	1	2	3	4	5	6	7	8
T1 ($N = 229$)										
1 Digital Communication	5.92	.65	(.70)							
2 Digital Collaboration	5.81	.80	.45**	(.77)						
3 Social Support	4.23	.65	.21**	.17**	(.72)					
4 Work Engagement	4.50	1.19	.16*	.15*	.29**	(.91)				
T2 ($N = 161$)										
5 Digital Communication	5.87	.66	.58**	.42**	.25**	.14	(.71)			
6 Digital Collaboration	5.85	.81	.31**	.58**	.17*	.03	.46**	(.81)		
7 Social Support	4.11	.71	.15	.18*	.68**	.26**	.20*	.24**	(.75)	
8 Work Engagement	4.49	1.21	.17*	.07	.30**	.80**	.24**	.16*	.42**	(.93)

Notes. Digital communication and collaboration and work engagement were measured on a 7-point scale, social support was measured on a 5-point scale. Cronbach's α are the values in brackets. Missings were excluded listwise.
* $p < .05$. ** $p < .01$.

Table 3
Goodness-of-fit statistics comparing the stability model to models testing reversed lagged effects between digital competencies, social support, and work engagement.

Model	χ^2	*df*	$\Delta\chi^2(\Delta df)$	*NFI*	*IFI*	*CFI*	*RMSEA*
(1) Stability model	566.13	432		.83	.95	.95	.04
(2) Causality model	562.05	427	4.08(5)	.83	.95	.95	.04
(3) Reversed Causation model	564.53	427	1.60(5)	.83	.95	.95	.04
(4) Reciprocal model	557.91	420	8.22(12)	.83	.95	.95	.04

Notes. $N = 231$.
χ^2 = chi-square fit index, *df* = degrees of freedom, NFI = Normed Fit Index; IFI = Incremental Fit Index; CFI = Comparative-Fit-Index; RMSEA = Root-Mean-Square-Error-of-Approximation.
All chi-square difference tests compare with the stability model. None of the tests was significant.

4. General discussion

Our findings from two different studies contribute to the understudied area of digital competencies at work and extend the scope of previous work by examining the motivational processes during a pandemic. We were able to develop a reliable questionnaire measuring digital communication and collaboration competencies at work by combining CTT and IRT approaches. We then cross-validated the intended two-factor structure in a second sample. In our main study, the majority of our hypotheses about the motivational effects, based on the well-established JD-R model and COR theory, were not supported by our data, that was collected during the COVID-19 crisis. Still, our findings provide important insights into the motivational processes at work during this time. In a cross-lagged study with a sample of office-based workers, we found no evidence for positive effects of digital communication or collaboration competencies in terms of a resource, under the special circumstances caused by the COVID-19 pandemic. Our results neither provided evidence for personal and job resources influencing each other over time, nor effects between work engagement and job or personal resources over time. In contrast, we found high stabilities of the variables at two times during the COVID-19 pandemic, indicating the maintenance of high levels of digital competencies, and work engagement, despite the crisis.

Therefore, we can conclude, that digital competencies and social support do not boost work engagement during the COVID-19 crisis – at least not for the mainly office-based workers included in our study at two time points during different phases of the pandemic. Yet, our findings bear important theoretical and practical implications for digital communication and collaboration competencies at work and for maintaining the motivation of workers during times of crisis.

4.1. Theoretical implications

By developing a measurement instrument for digital communication and collaboration competencies at work, we contribute to the existing research by refining the construct. Whereas most prior studies on digital competencies used imprecise definitions and terminology describing different constructs under the same terms (overview in Oberländer et al., 2020), we provide a clear definition and scope of the construct. In particular, our findings support that digital communication and collaboration competencies are two separate but highly related dimensions of digital competencies. Therefore, our results add a new perspective to prior conceptualizations of digital communication and collaboration competencies that focused on their overlapping content and often merged these two dimensions (Murawski & Bick, 2017). By providing a reliable and valid assessment tool for research and practice, we hope to enable further research adding to the knowledge about digital competencies at work that is much needed (e.g., Murawski & Bick, 2017).

The stability coefficients in our study imply that prior results on the

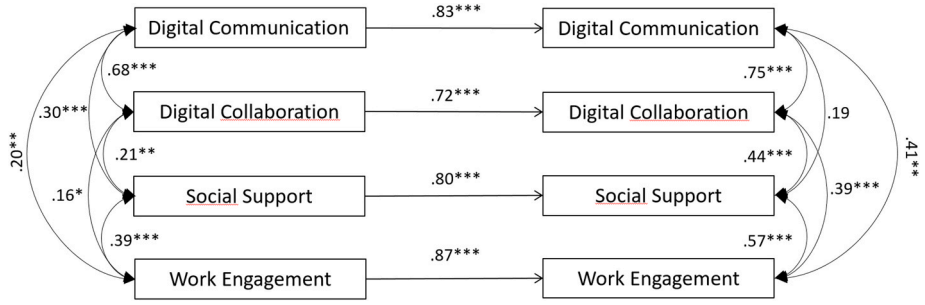

Fig. 2. Structure analysis model of the stability model (SEM).
Notes. $N = 231$. The results depicted are standardized values.
* $p < .05$. ** $p < .01$. *** $p < .001$.

stability of work engagement over time can be replicated in times of COVID-19 and that our results about missing time-lagged or reciprocal effects between study variables suggest that we need new models or theories to explain their interplay in times of crisis. In detail, our results showed that stability coefficients overall were relatively high. Besides a high level of digital communication and collaboration competencies across the two measurement points during the COVID-19 pandemic, workers who reported high work engagement at T1 also reported high work engagement at T2. The latter seems in line with prior findings for a high stability of work engagement even for longer periods than the one implemented in the current study (e.g., Seppälä et al., 2014). Also, the meta-analysis of Young et al. (2018) supports the high stability of work engagement, given that personality variables were able to explain 48% of the variance in work engagement. Moreover, Mauno et al. (2007) found that work engagement is generally higher in professionals compared to less professional groups. As our sample mainly consisted of white-collar workers with a high percentage of academic degrees, this could be another explanation for these results. However, results about the stability or variation of work engagement during the COVID-19 pandemic seem to be inconsistent. While our findings of high levels of work engagement during the pandemic seem to match results reported from Spanish frontline healthcare workers in March and April 2020 (Gomez-Salgado et al., 2021), Dutch employees reported a significant decrease in work engagement between January and May 2020 (Syrek et al., 2021). An explanation for these varying findings could be that the time frames of data collection were chosen differently, with different measures and actions taken in different countries. However, in particular, concerning the issue of time lags, the field requires detailed theories that can provide explanations and guidance about temporal issues at work (Weigelt et al., 2021).

Even though our results provide no support for the role of digital communication and collaboration competencies as personal resources boosting work engagement, it is too early to reject their potentially positive role concerning work motivation or outcomes in the current work situation. Significant correlations at each time point of the main study show that there are important relationships between these competencies and work engagement. Moreover, within the JD-R model, resources are also expected to contribute to goal achievement and foster personal learning and development (Demerouti et al., 2001). It could be that digital communication and collaboration competencies are especially beneficial as personal resources to gain knowledge and promote learning of such skills that are much needed at work during a pandemic. This seems in line with van Laar et al. (2019), who outlined how digital competencies as 21st-century skills are pivotal for learning and knowledge creation at work nowadays. Furthermore, it could be that the effects of digital competencies on other resources or motivational variables during COVID-19 depend on other variables. Recent findings suggest a role of prior experience in working from home (Kniffin et al., 2021), social support of the partner, or having younger kids at home (Meyer et al., 2021; Syrek et al., 2021). Besides, the JD-R model offers a range of alternative options on how personal resources can affect motivation and work outcomes, for example, in terms of a moderating role (overview in Schaufeli & Taris, 2014). However, neither the JD-R model nor the COR theory offer a systematic indication on which role would be appropriate but refer to additional theories to answer this question. Unfortunately, though, the literature on the theoretical construct of digital competencies is scarce and diverse (Murawski & Bick, 2017). Therefore, further systematic research on the construct of digital competencies is needed to expand existing knowledge about possible combined effects with current demands and resources at work. Our findings and measurement instrument form a basis to investigate potential effects on motivation or well-being comprehensively in the future, contributing to much-needed theory development in this field. So far, evidence about the particular role of competencies as personal resources in the motivational and health process outlined in the JD-R model is scarce.

In our data, we did not find evidence for social support and digital communication or collaboration competencies influencing each other over time. Moreover, our study did not provide evidence for the well-known reciprocal effects between social support and work engagement in times of crisis (Xanthopoulou et al., 2008). Especially in the complex and demanding situation of a pandemic, additional variables should be considered to display the combined impact of different resources in the motivational process. Examples could be person variables (e.g., need for autonomy, Van Yperen et al., 2014) or effective strategies to deal with specific technological demands or to facilitate job crafting (e.g., Harju et al., 2016). In a recent study, Hakanen et al. (2021) showed that the three job resources skill discretion, job feedback, and team empowerment are the most important drivers of work engagement among the eight job resources they looked at. Therefore, these resources could also be more important for the level of work engagement during the pandemic. However, neither social support nor digital communication and collaboration competencies were included in their study, and data were collected before the pandemic. Furthermore, the JD-R model does not offer a theoretical frame to decide which resource is helpful to cope with which demand. On top, the COVID-19 pandemic is an unprecedented crisis and can be seen as a new demand on its own within the JD-R model. Additionally, Syrek et al. (2021) argue that forced working from home full-time during the crisis can be interpreted as a threat that impairs important resources, such as social support, needed to handle the demands effectively. Therefore, it is unclear yet which resources are helpful in dealing with the impact of COVID-19 on work.

We found a significant decrease in social support from T1 to T2, which is in line with findings of other studies during the pandemic (Anicich et al., 2020; Meyer et al., 2021; Syrek et al., 2021). The decline might be explained by the difficulties of having informal chats at work while working from home. In contrast to the countless occasions where workers meet at the hallways or coffee kitchens in office buildings, workers have to take the time and energy to deliberately reach out for informal chats with colleagues to get social support when working from home. Already prior studies show that a shift from office-based work to virtual work leads to an unsatisfied need for social connection or lack of social support (Zhang, 2016). This could be even more so after the outbreak of the COVID-19 pandemic required workers to avoid face-to-face meetings at all, contributing to a less important role of social support as potential job resource as we found in this research. Another explanation could be offered by the phenomenon of zoom fatigue (Fauville et al., 2021). Workers are exhausted by the number of video calls that are scheduled already and think twice if they would start another call to ask for social support. Furthermore, as we did not differentiate between co-worker and supervisor support but used an overall measure for social support, it could also be that these different potential sources of social support had different effects in the pandemic work situation (Jolly et al., 2020). Also, we did not measure social support by the partner that Meyer et al. (2021) showed to have a significant main effect on exhaustion during the pandemic, but only for women.

4.2. Practical implications

In terms of practical implications, our questionnaire can help managers and organizations to assess and monitor current levels of digital communication and collaboration competencies of their employees for optimal support in developing their potential also during times calling for high levels of such competencies.

Our study provides evidence that workers with high shares of office tasks stay highly motivated despite such difficult and unpredictable circumstances and working from home during a pandemic, with no indication for potential negative effects. We found that a high initial level of work engagement stays stable, even in times of crisis. This is in line with prior findings: Schaufeli et al. (2009) found that changes in demands do not affect future levels of work engagement as much when

the initial level of work engagement was high. High stable work engagement can have positive effects, for individuals and organizations, leading to improved job performance and more personal and job resources (e.g., job feedback or team empowerment) over time (Bakker & Demerouti, 2008; Hakanen et al., 2021). Thus, organizations should consider improving work engagement for all workers at all times, and not just in highly skilled professionals or in times of crisis.

In our study, we found that workers rated their social support to be high at both times of measurement during the crisis, even though we found a significant decrease in social support over time. These findings imply that it is especially important to help those workers working from home not to feel isolated but keep socially connected with others at work. As long as workers cannot meet each other naturally in the office environments, for example in the coffee kitchen, there is a pressing need for other possibilities to have informal chats and bond with colleagues. Managers should be aware of this and build up social support systems especially for those who perceive social support to be low.

On the bright side, digital communication and collaboration competencies were rated as extraordinarily high and did not show a decrease over time in our study. These findings imply that situational demands during the pandemic do not seem to have the expected negative effects on personal resources of workers. Rather, workers stayed motivated in resourceful work environments despite demanding challenges in times of crisis. Remote work environments are becoming more common, a trend that is likely to last beyond the working from home policies to condemn the COVID-19 pandemic. The experiences made during this time of extensive practice of working from home could help workers to manage upcoming challenges in the future. However, even though workers rated their digital communication and collaboration competencies to be sufficiently high in our study, they could profit from further learning and training their competencies to be prepared for the challenges of the future world of work.

4.3. Limitations and further research

Our research inevitably has limitations that suggest directions for future research. We collected data in two samples of German workers, before and during two critical phases in the course of the COVID-19 pandemic. Although the unique timeframe of the data collection is a strength of this research, concerns about the generalizability of the results could be raised. However, despite the extraordinary circumstances during data collection, we believe our findings yield important insights into the motivational processes at work. Future studies might benefit from integrating data from different countries and cultural backgrounds, at different time points and under varying working circumstances of the crisis. Also, the question remains, if our anticipated effects will emerge again, once the pandemic is over. Moreover, we have to acknowledge that working from home was probably mandatory and non-optional for most of the participants, but we do not have details about the individual working circumstances, job characteristics, or specific organizational regulations from the moment of data collection.

Another limitation forms the exclusive reliance on self-report measures. Although they are a valid technique to draw conclusions on the inner perceptions of the individuals about their resources, additional objective measures should be considered in future research. In particular, given that prior research has shown that digital competencies measured with self-assessment overrate the actual competencies of undergraduates (McCourt Larres et al., 2003), future research could complement these by alternative measurement methods (e.g., colleagues or supervisors ratings, knowledge or performance tests). Also, our sample size did not allow us to test for differences in further subgroups.

Although we adjusted the answering format for our scales, the levels of digital communication and collaboration competencies measured in both our studies were very high, indicating potential ceiling effects. This might be due to a potential self-selection bias of the participants as the studies were conducted online and aimed at professionals with office-based jobs. This could have affected the external validity of our measure (Schulze et al., 2017). It could also be possible that workers with high levels of digital communication and collaboration competencies, who were also highly motivated and dealing well with working from home during the pandemic, were more likely to participate in our surveys. Therefore, future studies should strive for more diverse samples, for example, also aiming at less professional workers to expand the existing knowledge about digital competencies and motivational processes for different kinds of workers.

5. Conclusions

In sum, we developed a valid measurement of digital communication and collaboration competencies at work but found no evidence for these competencies to function as personal resources in times of crisis. We neither found the well-known reciprocal effects between social support and work engagement nor the resources influencing each other over time as expected based on theories and models developed to explain the motivation of employees before the pandemic. Thus, the results of our studies raise the question of whether the COVID-19 pandemic ended the world of work, as we know it in terms of effects of resources on work engagement as proposed by the JD-R model.

Credit author statement

Maren Oberländer: Conceptualization, Methodology, Formal analysis, Investigation, Data Curation, Writing – Original Draft, Writing – Review & Editing. **Tanja Bipp:** Conceptualization, Methodology, Writing – Review & Editing, Supervision, Funding acquisition.

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Declaration of competing interest

None.

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Appendix A. Supplementary data

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