New Normal, but Good Normal?
Three Studies on Employees’ Adaption to
the Digitalization, the COVID-19
Pandemic, and Mobile Work

Doctoral thesis for obtaining the
academic degree Doctor of Social Sciences
(Dr. rer. soc.)

submitted by
Sophia Teresa Zimmermann

at the

Universität Konstanz

Faculty of Politics – Law – Economics
Department of Politics and Public Administration

Konstanz, 2022
“Science is a way of life. Science is a perspective. Science is the process that takes us from confusion to understanding in a manner that’s precise, predictive and reliable — a transformation, for those lucky enough to experience it, that is empowering and emotional.”

Brian Greene
Acknowledgements

Academia is harsh, time-consuming, frustrating and not well-paid, they say. Well... that’s true, I guess, but academia can also be very satisfying, empowering, and truly inspiring. I really enjoyed my journey in academia. Of course, I struggled from time to time, but my dissertation was a great experience that I cherish and would not want to miss in my life. What made my dissertation so special were the lovely people who accompanied and supported me throughout this journey. Therefore, from the bottom of my heart, thank you.

I would like to express sincere gratitude to my advisors. Florian, your enthusiasm for our research and your characteristic way of bubbling over with ideas was truly inspiring. You offered prudent advice in all aspects of academia and empowered me to grow professionally and personally ever since my bachelor studies. Thank you for always having my back in all kinds of challenging situations. Sabine Boerner, you taught me how to write a concise theoretical argument, and I was able to pass on much of what I have learned from you to my students in my own teaching. Stephan, I really enjoyed presenting my work at our workshops and your feedback and ideas always had great value for advancing my research.

My gratitude also goes to my former and current colleagues. Max and Ben, I really appreciated your constructive support when I struggled with my methods. Kilian, thank you for checking in with me every day with countless phone calls, for those precious tea parties, and for always sharing the ups and downs of being a doctoral student. Gabi, you were my savior in need when filling in travel expense reports and the best cocktail companion — we had such a laugh together, didn’t we?

I would also like to thank all those outside work, whose support, and encouragement made this dissertation possible. To my lovely girlfriends — Elena, Alina and Julia — you are a constant source of inspiration and warmth to me. Also to Max and Johannes, your advice on both my work and personal life is always spot on. Thank you for accompanying me for
so long and sharing so many memorable escapades with me.

I would like to thank my family. Especially my parents, Cornelia and Thomas, and my sister, Tina, for always standing by my side throughout my life. Thank you for your unconditional support and love. And my uncle Stephan who always took great interest in my research and could relate to the challenges as a researcher. Also a big thank you for my soon-to-be parents in law, Ilona and Norbert, for welcoming me into their family.

Finally, my very special thanks to the love of my life, Simon. Thank you — for everything.

Yours, Sophia
Summary

The intertwined and mutually reinforcing workplace dynamics of the digitalization, the COVID-19 pandemic, and the flexibilization of the location of work in the form of telecommuting have kept the world of work on its toes and substantially altered the individual experience of work. This dissertation conducts three empirical studies to advance our understanding of employees’ adaptive responses to the transformational change driven by these workplace dynamics in organizations.

Focusing on employees’ adaption to the digitalization, Study I contributes to clarifying the concept of digital competence at work. Based on a sample of 218 employees and 17 leaders from a German technology company, the study uncovers that digital fluency, which consists of digital knowledge and digital self-efficacy, enables employees to exert enhanced digital work performance — a positive effect that can even be enhanced by modeling leaders who themselves have a high level of digital fluency. Study II considers employees’ response to the COVID-19 pandemic, exploring employees’ age and extent of working from home as key context factors that influence employees’ strain reaction to the daily COVID-19 surge. However, the proposed relationships are not supported by an eight-day diary study with 389 participants. Study III offers a better understanding of resource-enhancing ways of working in a telecommuting context. Results from a panel study of 368 German employees tracked over 1.5 years suggest that employees perform best when they telecommute only a little or a lot throughout the week, while they perform worst when they work in a hybrid form at intermediate levels of telecommuting and regularly switch between work locations during the week.

Overall, the findings of the dissertation highlight the complexity and magnitude of change in organizations which employees need to adapt to in order to thrive in the future. The insights into employees’ adaptive responses to the digitalization, COVID-19 pandemic and telecommuting can inform practitioners about shaping a future of work that creates a new,
yet good, normal for employees.
Zusammenfassung


Insgesamt verdeutlichen die Ergebnisse der Dissertation die Komplexität
und das Ausmaß des organisationalen Wandels, an den sich Mitarbeitenden anpassen müssen, um in Zukunft erfolgreich zu sein. Die Erkenntnisse über ihre adaptive Reaktion auf die Digitalisierung, die COVID-19 Pandemie und an die mobile Arbeit geben Organisationen und ihren Führungskräften wertvolle Anhaltspunkte, um eine neue, aber dennoch gute Normalität in der Zukunft für Mitarbeitende zu schaffen.
# Contents

Acknowledgements                                      VII  
Summary                                               IX  
Zusammenfassung                                      XI  
List of Figures                                       XVII  
List of Tables                                        XIX  

1 General Introduction  
1.1 Relevance and Research Purpose  
1.2 Literature Review and Research Questions  
   1.2.1 Consequences of the Digitalization  
   1.2.2 Consequences of the COVID-19 Pandemic  
   1.2.3 Consequences of Telecommuting  
   1.2.4 Research Gaps and Research Questions  
1.3 Dissertation Outline and Chapter Structure  

2 Digital Fluency – A Key Employee Resource to Perform in the Digital Age?  
2.1 Introduction  
2.2 Theory Development  
   2.2.1 Digital Fluency  
   2.2.2 Digital Fluency: a Determinant of Digital Work Performance  
   2.2.3 Leaders’ and Coworkers’ Digital Fluency: Potential Contextual Factors in Explaining Digital Work Performance  
2.3 Methods and Results  
   2.3.1 Study 1  
       2.3.1.1 Digital Fluency Scale Development  
       2.3.1.2 Data Collection and Sample  
       2.3.1.3 Results  
           2.3.1.3.1 Internal Validity  
           2.3.1.3.2 Discriminant Validity  

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acknowledgements</td>
<td>VII</td>
</tr>
<tr>
<td>Summary</td>
<td>IX</td>
</tr>
<tr>
<td>Zusammenfassung</td>
<td>XI</td>
</tr>
<tr>
<td>List of Figures</td>
<td>XVII</td>
</tr>
<tr>
<td>List of Tables</td>
<td>XIX</td>
</tr>
<tr>
<td>1 General Introduction</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Relevance and Research Purpose</td>
<td>1</td>
</tr>
<tr>
<td>1.2 Literature Review and Research Questions</td>
<td>6</td>
</tr>
<tr>
<td>1.2.1 Consequences of the Digitalization</td>
<td>6</td>
</tr>
<tr>
<td>1.2.2 Consequences of the COVID-19 Pandemic</td>
<td>9</td>
</tr>
<tr>
<td>1.2.3 Consequences of Telecommuting</td>
<td>12</td>
</tr>
<tr>
<td>1.2.4 Research Gaps and Research Questions</td>
<td>15</td>
</tr>
<tr>
<td>1.3 Dissertation Outline and Chapter Structure</td>
<td>16</td>
</tr>
<tr>
<td>2 Digital Fluency – A Key Employee Resource to Perform in the Digital Age?</td>
<td>21</td>
</tr>
<tr>
<td>2.1 Introduction</td>
<td>23</td>
</tr>
<tr>
<td>2.2 Theory Development</td>
<td>26</td>
</tr>
<tr>
<td>2.2.1 Digital Fluency</td>
<td>27</td>
</tr>
<tr>
<td>2.2.2 Digital Fluency: a Determinant of Digital Work Performance</td>
<td>29</td>
</tr>
<tr>
<td>2.2.3 Leaders’ and Coworkers’ Digital Fluency: Potential Contextual Factors in Explaining Digital Work Performance</td>
<td>30</td>
</tr>
<tr>
<td>2.3 Methods and Results</td>
<td>32</td>
</tr>
<tr>
<td>2.3.1 Study 1</td>
<td>33</td>
</tr>
<tr>
<td>2.3.1.1 Digital Fluency Scale Development</td>
<td>33</td>
</tr>
<tr>
<td>2.3.1.2 Data Collection and Sample</td>
<td>34</td>
</tr>
<tr>
<td>2.3.1.3 Results</td>
<td>36</td>
</tr>
<tr>
<td>2.3.1.3.1 Internal Validity</td>
<td>36</td>
</tr>
<tr>
<td>2.3.1.3.2 Discriminant Validity</td>
<td>37</td>
</tr>
</tbody>
</table>
2.3.2 Study 2 ........................................ 40
  2.3.2.1 Methods ..................................... 40
    2.3.2.1.1 Data Collection and Sample .......... 40
    2.3.2.1.2 Measures ................................ 42
      2.3.2.1.2.1 Employees’ Digital Fluency .... 42
      2.3.2.1.2.2 Leaders’ Digital Fluency . 42
      2.3.2.1.2.3 Coworkers’ Digital Fluency .. 42
      2.3.2.1.2.4 Digital Work Performance .... 43
      2.3.2.1.2.5 Controls ............................. 43
    2.3.2.1.3 Analytical Procedure ................. 44
  2.3.2.2 Results .................................... 45
    2.3.2.2.1 Descriptive Statistics .............. 45
    2.3.2.2.2 Hypotheses Testing ................. 46
2.4 Discussion ........................................ 50
  2.4.1 Theoretical Implications .................... 51
  2.4.2 Limitations and Future Research .......... 53
  2.4.3 Practical Implications ........................ 54

3 Local COVID-19 Infections and Daily Employee Exhaustion: A Diary Study of Moderating Factors 57
  3.1 Introduction ..................................... 59
  3.2 Theory Development .............................. 62
    3.2.1 Effect of Local COVID-19 Cases on Emotional Exhaustion ..................... 62
    3.2.2 Employee Age and the Effect of Local COVID-19 Cases on Emotional Exhaustion ....... 64
    3.2.3 Working from Home and the Effect of Local COVID-19 Cases on Emotional Exhaustion ........ 65
    3.2.4 Interplay between Age, the Extent of Working from Home and the Effect of Local COVID-19 Cases on Emotional Exhaustion .......... 66
  3.3 Methods .......................................... 67
    3.3.1 Procedure and Participants ............... 67
    3.3.2 Measures ..................................... 68
      3.3.2.1 Age ................................... 68
      3.3.2.2 Daily COVID-19 Cases ................. 68
      3.3.2.3 Daily Emotional Exhaustion ......... 69
      3.3.2.4 Daily Extent of Working from Home ... 70
    3.3.3 Data Analysis ................................ 70
  3.4 Results .......................................... 71
    3.4.1 Descriptive Statistics ..................... 71
    3.4.2 Hypotheses Testing ......................... 72
    3.4.3 Sensitivity Test ............................. 73
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.5 Discussion</td>
<td>73</td>
</tr>
<tr>
<td>3.5.1 Theoretical Implications</td>
<td>75</td>
</tr>
<tr>
<td>3.5.2 Limitations and Future Research</td>
<td>75</td>
</tr>
<tr>
<td>3.5.3 Practical Implications</td>
<td>77</td>
</tr>
<tr>
<td>3.6 Conclusion</td>
<td>77</td>
</tr>
<tr>
<td>4 New Normal, but Good Normal? Testing the Effect of a Hybrid Way of Working on Employee Work Effectiveness</td>
<td>79</td>
</tr>
<tr>
<td>4.1 Introduction</td>
<td>81</td>
</tr>
<tr>
<td>4.2 Theory Development</td>
<td>86</td>
</tr>
<tr>
<td>4.2.1 The Curvilinear Relationship between the Weekly Extent of Telecommuting and Weekly Work Effectiveness</td>
<td>86</td>
</tr>
<tr>
<td>4.2.2 The Moderating Role of General Self-goal Setting</td>
<td>90</td>
</tr>
<tr>
<td>4.3 Method</td>
<td>93</td>
</tr>
<tr>
<td>4.3.1 Procedure and Participants</td>
<td>93</td>
</tr>
<tr>
<td>4.3.2 Measures</td>
<td>94</td>
</tr>
<tr>
<td>4.3.2.1 Weekly Extent of Telecommuting</td>
<td>94</td>
</tr>
<tr>
<td>4.3.2.2 Weekly Work Performance</td>
<td>94</td>
</tr>
<tr>
<td>4.3.2.3 Weekly Emotional Exhaustion</td>
<td>94</td>
</tr>
<tr>
<td>4.3.2.4 Self-goal Setting</td>
<td>95</td>
</tr>
<tr>
<td>4.3.2.5 Controls</td>
<td>95</td>
</tr>
<tr>
<td>4.3.3 Data Analysis</td>
<td>96</td>
</tr>
<tr>
<td>4.4 Results</td>
<td>97</td>
</tr>
<tr>
<td>4.4.1 Descriptive Statistics</td>
<td>97</td>
</tr>
<tr>
<td>4.4.2 Hypotheses Testing</td>
<td>98</td>
</tr>
<tr>
<td>4.5 Discussion</td>
<td>104</td>
</tr>
<tr>
<td>4.5.1 Theoretical Implications</td>
<td>106</td>
</tr>
<tr>
<td>4.5.2 Limitations and Future Research</td>
<td>108</td>
</tr>
<tr>
<td>4.5.3 Practical Implications</td>
<td>109</td>
</tr>
<tr>
<td>4.6 Conclusion</td>
<td>110</td>
</tr>
<tr>
<td>5 General Discussion</td>
<td>111</td>
</tr>
<tr>
<td>5.1 Summary and Integration</td>
<td>111</td>
</tr>
<tr>
<td>5.2 Overall Limitations and Avenues for Future Research</td>
<td>115</td>
</tr>
<tr>
<td>5.3 Practical Implications</td>
<td>119</td>
</tr>
<tr>
<td>5.4 Overall Conclusion</td>
<td>121</td>
</tr>
<tr>
<td>A Appendix Chapter 2</td>
<td>123</td>
</tr>
<tr>
<td>A.1 Further Measurement Information</td>
<td>125</td>
</tr>
<tr>
<td>A.1.1 Measures</td>
<td>126</td>
</tr>
<tr>
<td>A.1.1.1 Resistance to Change</td>
<td>126</td>
</tr>
<tr>
<td>A.1.1.2 Locus of Control</td>
<td>126</td>
</tr>
<tr>
<td>A.1.1.3 General Self-efficacy</td>
<td>127</td>
</tr>
</tbody>
</table>
A.1.1.4 Computer Self-efficacy .................................. 127
A.1.1.5 In-role Performance ................................. 127
A.1.1.6 Digital Productivity ................................. 128
A.1.1.7 Digital Work Performance ....................... 128

Declaration of Authorship .................................... 135

References ....................................................... 137
## List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Overview of Dissertation Structure</td>
<td>19</td>
</tr>
<tr>
<td>2.1</td>
<td>Conceptual Model Study 1</td>
<td>26</td>
</tr>
<tr>
<td>2.2</td>
<td>Impact of Leaders’ Digital Fluency on the Positive Relationship between Em-</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>ployees’ Digital Fluency and their Digital Work Performance in the Company</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Sample (Study 2)</td>
<td></td>
</tr>
<tr>
<td>3.1</td>
<td>Conceptual Model Study 2</td>
<td>62</td>
</tr>
<tr>
<td>4.1</td>
<td>Conceptual Model Study 3</td>
<td>85</td>
</tr>
<tr>
<td>4.2</td>
<td>Curvilinear Effect of the Weekly Extent of Telecommuting on Weekly Work Per-</td>
<td>103</td>
</tr>
<tr>
<td></td>
<td>formance</td>
<td></td>
</tr>
<tr>
<td>4.3</td>
<td>Curvilinear Effect of the Weekly Extent of Telecommuting on Weekly Emotional</td>
<td>103</td>
</tr>
<tr>
<td></td>
<td>Exhaustion</td>
<td></td>
</tr>
</tbody>
</table>
# List of Tables

2.1 The Exact Wording of the Digital Fluency Scale .......................... 34
2.2 Descriptive Statistics and Internal Validity Estimates of the Digital Fluency Scale in the MTurk Sample (Study 1) .................. 37
2.3 CFA Results for Digital Fluency ........................................ 37
2.4 Discriminant Validity of Digital Fluency in the MTurk Sample (Study 1) ................................................................. 39
2.5 Descriptive Statistics and Correlations in the Company Sample (Study 2) ................................................................. 48
2.6 Regression on Employees’ Digital Work Performance in the Company Sample (Study 2) ................................................................. 49
3.1 Means, Standard Deviations, and Correlations of Study Variables ................................................................. 71
3.2 Multilevel Model Predicting Daily Emotional Exhaustion .......... 74
4.1 Means, Standard Deviations, and Correlations of Study Variables ................................................................. 100
4.2 Multilevel Model predicting Within-person Weekly Work Performance ................................................................. 101
4.3 Multilevel Model predicting Within-person Weekly Emotional Exhaustion ................................................................. 102
A.1 Descriptive Statistics of the Resistance to Change Scale .... 129
A.2 Descriptive Statistics of the Locus of Control Scale .......... 130
A.3 Descriptive Statistics of the Locus of Control Scale (continued) ................................................................. 131
A.4 Descriptive Statistics of the General Self-efficacy Scale .... 131
A.5 Descriptive Statistics of the Computer Self-efficacy Scale .... 132
A.6 Descriptive Statistics of the Performance Measures .......... 133
1

General Introduction

1.1 Relevance and Research Purpose

The world of work has experienced exponential change which has profoundly transformed employees’ lives within and beyond work. Over the past decade, a set of ground-breaking, emerging technologies has signaled the start of the Fourth Industrial Revolution (World Economic Forum, 2020). Technologies, such as cloud and mobile computing, big data and machine learning, sensors and intelligent manufacturing or advanced robotics and drones, have led to a quantum leap into a new future of work in which the way organizations create and capture value is fundamentally different (Cascio & Montealegre, 2016; Vuori et al., 2019). Consider, for example, the variety of new business models that have been shooting out of the ground like mushrooms, like PayPal, Uber, WhatsApp, Instagram, Airbnb and Babbel.

Organizations appear to benefit from adopting technology-based work arrangements in terms of increased operational efficiency (Rosin et al., 2020), performance (Kobelsky et al., 2008; van Ark, 2015), productivity (Tambe & Hitt, 2012), and greater market flexibility (Rosin et al., 2020). Yet to capture these opportunities created by technologies, many companies across the private sector appear to have embarked on a reorientation
of their strategic direction (World Economic Forum, 2020).

The World Economic Forum (2020) expects that, by 2025, the capabilities of machines and algorithms will be broadly employed, and the work hours performed by machines will match the time spent working by employees. As a result, organizations profoundly transform tasks, jobs and skills: 43 percent of businesses surveyed by the World Economic Forum (2020) indicate that they are set to reduce their workforce due to technology integration, 41 percent plan to expand their use of contractors for task-specialized work, and 34 percent plan to expand their workforce due to technology integration. Furthermore, 73 percent of the surveyed companies aim to provide reskilling and upskilling opportunities to the majority of their staff, aware of the fact that, by 2025, 44 percent of the skills that employees will need to perform their roles effectively will change (World Economic Forum, 2020). Consequently, the increasing digitalization of the workplace appears to have led to a redefinition of business structures and processes (van Zoonen et al., 2016) — even more, it has triggered a structural change in the labor market with a possibility of mass job displacement and skill shortages.

Yet not enough, the outbreak of the novel COVID-19 virus at the beginning of 2020 has accelerated the fundamental change in workplace beyond anything we could have imagined. The virus transmission mechanisms urged governments and organizations to take drastic measures to contain the exponential spread of the virus, such as limiting social contacts, physical distancing and wearing face masks (World Health Organization, 2021). The restrictions even extended to complete societal and economic shutdowns, as in March and April 2020, when schools, universities, cultural institutions, retail and restaurants closed and any kind of social interaction was limited (Die Bundesregierung, 2020). Consequently, the only safe way left to purchase goods and connect with people, whether at work, in education, or socially was through digital technologies.

In this way, the pandemic has amplified the impact of the digitalization
on the workplace. A McKinsey global survey of 899 C-level executives and senior managers conducted from July 7 to 31, 2020 illustrates this reinforcing effect: respondents reported that their companies have accelerated the digitalization of their customer and supply-chain interactions and of their internal operations by three to four years. Moreover, the share of digital or digitally enabled products in their portfolios has even accelerated by seven years (LaBerge et al., 2020).

Above and beyond the accelerated digitalization, the pandemic has led to a large-scale shift towards telecommuting which is defined as “an alternative work arrangement in which employees perform tasks elsewhere that are normally done in a primary or central workplace, for at least some portion of their work schedule, using electronic media to interact with others inside and outside the organization” (Gajendran & Harrison, 2007, p. 1525). All of a sudden thousands of employees worldwide were sent to work from home as telecommuting proved to be an effective way for organizations to facilitate social distancing and protect their employees from infection, while maintaining business operations as best as possible (Alipour et al., 2020).

The following OECD data illustrate how significant this worldwide shift towards telecommuting has been: 47 percent of employees in France and the United Kingdom telecommuted during the first lockdown periods form March to May 2020. Thus, in France, telecommuting more than doubled compared to one year before, increasing by 25 percent. In the United Kingdom, telecommuting in April 2020 increased by 20 percent which was 1.8 times the level before the pandemic. Australia also reached the same rate by December 2020. In Australia, teleworking in December 2020 was, thus, 1.5 times the level before the pandemic which corresponds to a 15 percent increase. Even in Japan, which did not institute a nationwide lockdown in 2020, telecommuting rates increased substantially from 10 percent in December 2019 to almost 28 percent in May 2020, although stayed lower than in the aforementioned countries (OECD, 2021).
Consequently, the COVID-19 pandemic has been a catalyst for telecommuting to evolve from a niche phenomenon to one that affects a large proportion of the workforce. Now, well into the pandemic, telecommuting even has become the “new normal”. Employees seem to particularly welcome hybrid models of remote work (Barrero et al., 2021; Bloom, 2020), where they telecommute at an intermediate level and move rather freely between work locations, from the office to another location, and back again to do their work (Halford, 2005). Yet the increased flexibility in the location of work has also sparked a discussion among employers about the right handling of telecommuting in the wake of the pandemic (Flint, 2020; Thomas & Cutter, 2021). Negotiating and crafting a post-pandemic future of work will, therefore, be, and already is, a major challenge for organizations.

Taken together, the twin forces of the digitalization and the COVID-19 pandemic have unleashed a storm of change that has transformed the way employees do their jobs, the skills they need, and even where they work. Therefore, employees face a wholesale shift in working practices with new demands and profoundly changing conditions. Yet how can employees sustain their effectiveness in the face of such transformational, exponential change?

This dissertation aims to pursue this question by investigating employees’ adjustment to the organizational change driven by the digitalization, the pandemic itself and the accompanying flexibilization of the location of work in form of telecommuting. I draw on existing frameworks of organizational change (Oreg et al., 2011; van den Heuvel et al., 2010) and conceptualize employee adjustment to change as comprising work-related (i.e., work performance) and health-related (e.g., well-being) indicators of employee effectiveness. Therefore, this dissertation focuses on employees’ ability to fulfill their task requirements (Sonntag et al., 2008) and protect themselves from emotional exhaustion — a state of intensive physical, emotional and cognitive strain (Maslach & Leiter, 2008) to capture
employees’ effectiveness in adapting to the digitalization, the COVID-19 pandemic and telecommuting.

Individual work performance and emotional exhaustion are of high relevance for an organization as a whole, but also for the individuals working within it. Considering individual work performance, organizations need highly performing employees in order to meet their goals, to deliver the products and services they specialized in, and finally to achieve competitive advantage (Sonnentag & Frese, 2002). Moreover, performance appears to be important for individuals, too. Accomplishing tasks and performing at a high level can be a source of satisfaction, with feelings of mastery, self-efficacy and pride (Bandura, 1997; Kanfer & Ackerman, 2005). Moreover, performance, if it is recognized by others within the organization, is often rewarded by financial and other benefits (Sonnentag & Frese, 2002). Furthermore, performance seems to be a major prerequisite for future career development and success in the labor market. High performing employees have been found to get promoted more easily and generally have better career opportunities than low performers (van Scotter et al., 2000).

Emotional exhaustion is “the central quality of burnout” (Maslach et al., 2001, p. 402) and has profound implications for employees’ well-being and work-related behavior. For example, emotional exhaustion has been found to promote absenteeism, turnover (Swider & Zimmerman, 2010), and attrition (Carson et al., 2010) and to mitigate organizational citizenship behavior towards the organization and the leader (Croppanzano et al., 2003). Therefore, employee performance and emotional exhaustion are considered crucial dimensions of employee effectiveness in adapting to the digitalization, the COVID-19 pandemic and telecommuting.

To provide a more holistic understanding of employees’ adjustment to the recent upheavals in the workplace, I begin by reviewing the research on work-related and health-related consequences of the digitalization, the COVID-19 pandemic and telecommuting on employees and identify cur-
rent challenges. Based on the review, I identify shortcomings in the re-
search done on these workplace dynamics and formulate three research
question, one for each workplace dynamic. These research questions form
the basis of this dissertation, which each question being examined in a
separate study.

1.2 Literature Review and Research Questions

1.2.1 Consequences of the Digitalization

The study of the consequences of the digitalization on employees is
dominated by research on the dark side of workplace technologies — that
is the unintended, negative consequences of technology use, which appear
to be anxiety (A. L. Powell, 2013) or even phobia (Agogo & Hess, 2018),
distraction (Puranik et al., 2020), addiction (Salanova et al., 2013), and
technostress (Tarafadar et al., 2007). However, these dark side effects have
not been investigated in equal measure, with technostress by far the most
prominent area of the literature (Marsh et al., 2022).

Rooted in Lazarus and Folkman’s (1984) transactional model of stress
and coping, technostress is primarily considered as a distress process which
is set into motion by technology-related demands that employees appraise
as taxing or exceeding their resources and abilities to cope (Srivastava
et al., 2015; Tarafadar et al., 2018). According to Tarafadar et al. (2007),
such technology-related demands include overload, invasion, complexity,
insecurity, and uncertainty\(^1\). A recent meta-analysis (Gerdiken et al.,
2021) shows that technostress has significant detrimental effects on em-
ployee behavioral (i.e., innovation), attitudinal (e.g., turnover intentions,
job satisfaction) and health-related (i.e., job burnout, work-to-family con-
flict, techno exhaustion) outcomes.

\(^1\) Overload refers to the feeling to be forced to work more and faster due to technology. Invasion refers
to the feeling to be constantly connected and the experience of blurred boundaries due to technology.
Complexity refers to the feeling of being inadequate as far as technological skills are concerned. Insecurity
refers to the feeling of being threatened about losing one’s job as a result new technology. Uncertainty
refers to an unsettled feeling in the face of the incessant evolution of technologies (Tarafadar et al., 2007).
Yet recent research has started to acknowledge the bright side of technology use (Califf et al., 2020). As Benlian (2020, p. 1260) points out, “treating technology-related stress as uniformly bad may be an oversimplification because this type of stress often comes in many shapes”. Drawing from the challenge-hindrance stressor framework of the work stress literature (Cavanaugh et al., 2000; Crawford et al., 2010), technostress research has, therefore, started to distinguish technology-driven hindrance stressors which employees appraise as potentially hindering their personal development and accomplishments from technology-driven challenge stressors which employees rather appraise as opportunity that can promote their personal growth and achievement (Benlian, 2020; Califf et al., 2020; Maier et al., 2021; Tarafdar et al., 2018; Zhao et al., 2020). Employees are proposed to respond to hindrance and challenge stressors differently. Hindrance stressors are considered to create “bad stress”, that is distress, by posing an obstacle to task fulfillment, being a resource constraint, eliciting role or task ambiguity, and producing role or task conflicts (Benlian, 2020). In contrast, challenge stressors are considered to create “good stress”, that is eustress, by helping employees handle high workloads, meet challenging deadlines, improve their ICT knowledge and digital competencies, or solve complex problems (Benlian, 2020).

Although the research on the bright side of technology use appears to be in its infancy, pioneering studies (Benlian, 2020; Califf et al., 2020) provide some first indications that, indeed, technology-driven hindrance and challenge stressors tend to be associated with opposite employee outcomes. Califf et al. (2020) demonstrate that challenge (i.e., usefulness, involvement facilitation) and hindrance (i.e., unreliability, uncertainty, overload) technostressors evoke positive and negative psychological responses in employees, respectively, and that such responses are related to job satisfaction and attrition, which impact turnover intention. In the same vein, Benlian (2020) shows that on days when employees experience more technology-related challenge stressors at work, they are more likely to feel more positive affect at work, while on days when employees experi-
ence more technology-related hindrance stressors at work, they are more likely to feel more negative affect at work.

Together, the research on the dark side and the bright side of technology use has contributed to a holistic understanding of how technology-related stress unfolds from the perspective of an individual interacting with their technological environment. Central to this new holistic understanding appears to be employees’ appraisal of the technology-related conditions and the intrapersonal process through which employees decide how to respond either positively or negatively to the appraised demands (Califf et al., 2020).

A further strand of literature on the digitalization of the workplace that ties in with employees’ predisposition to respond negatively or positively to technological demands is the research on employees’ digital competence. Past research has highlighted digital competence as a valuable resource to cope with the changing demands in a digitalized work setting (Ala-Mutka, 2011; Ferrari, 2012; Ferrari et al., 2012). Furthermore, digital competence has been explored as a moderator of the technology-related distress-outcome relationships (Soucek & Moser, 2010; Tarafdar et al., 2015).

However, extant research appears to be ambiguous what digital competence really is and how it can be measured, since a recent literature review (Oberländer et al., 2020) reveals profound conceptual and methodological limitations of the digital competencies literature. In terms of conceptualization, extant frameworks (Ala-Mutka, 2011; Ferrari, 2012; Hatlevik, 2009; Mengual-Andrés et al., 2016) appear to considerably differ in content, scope and terminology, since they vary in the number of dimensions and basic assumptions of digital competence and the labels used to describe it. As Oberländer et al. (2020, p. 4) point out, the literature appears not only to be in “disagreement on the terminology for the same construct, but also on the structure of the concept behind the same term”. Considering empirical evidence, Oberländer et al. (2020, p. 5) highlight the doc-
umentation of the data collection, instruments used, and data analysis of most publications as “insufficient”. Furthermore, the digital competencies of workers appear to have rarely been subject to empirical investigation. Therefore, Oberländer et al. (2020, p. 5) “conclude that more scientific methods and rigorous scientific practice are needed to address DC [digital competence] at work”. They particularly encourage industrial and organizational psychologists to address this research gap.

In sum, researchers have explored the dual nature of the digitalization demonstrating that working with digital technologies is a double-edged sword with the potential for having opposite effects on employees. An individual characteristic that has been discussed to influence employees’ response to this digitalization paradox is digital competence. Yet further conceptual and methodological clarification appears to be needed to define the nature of digital competence.

1.2.2 Consequences of the COVID-19 Pandemic

Although research on the COVID-19 pandemic appears to be only in its infancy, a few pioneering studies have already provided some valuable insights into employees’ responses to the COVID-19 pandemic. These studies appear to have explored the consequences of the COVID-19 pandemic through different theoretical lenses. One strand of research (Fu et al., 2021; Hillebrandt & Barclay, 2022; Lin et al., 2021; D. Liu et al., 2021; Wee & Fehr, 2021) draws from appraisal theories, that is the transactional model of stress (Lazarus & Folkman, 1984) and events systems theory (Morgeson et al., 2015) or a combination thereof to explore employees’ responses to the COVID-19 crisis. This literature conceptualizes the COVID-19 pandemic as an external stressor or a stressful event closely related to employees’ work. Furthermore, the pandemic is considered in terms of its strength or severity proposing that employees’ behavioral and psychological responses to the stressor are determined by employees’ perception of its strength and thus its relevance which is reflected by the
empirical findings based on different methodological approaches\(^2\).

Employees appear to react to the pandemic with increased anxiety which in turn affects employees’ functioning (i.e., engagement, emotional exhaustion, work performance) (Fu et al., 2021) and also prompts employee cheating behavior (i.e., self-interested unethical behavior) (Hillebrandt & Barclay, 2022). Furthermore, employees appear to be less likely to speak their mind and share their opinions, since they suffer more and are more dependent on their supervisor (Wee & Fehr, 2021). Lastly, employees seem to perceive more job insecurity which in turn affects their emotional exhaustion, organizational deviance, and saving behavior (Lin et al., 2021).

Another strand of research (J. Hu et al., 2020; Shao et al., 2021) explores employees’ reactions to the COVID-19 crisis through the lens of the terror management theory (E. Becker, 1973; Greenberg et al., 1986). This literature conceptualizes the COVID-19 crisis as a salient mortality cue that primes employees with life’s fragility. Findings of time-lagged field studies (Shao et al., 2021), a daily diary study and experiments (J. Hu et al., 2020) indicate that employees react to this mortality salience with increased state and death anxiety. However, on the positive side, this literature indicates that employees can also respond toward the mortality-related threat placed by the pandemic in more adaptive ways. Shao et al. (2021) demonstrate that employees engage in helping behaviors towards their coworkers as a result of their positive death reflection triggered by the pandemic.

Consequently, research on the COVID-19 pandemic indicates that the COVID-19 pandemic severely affects employees, thereby corroborating the limited organizational behavior research on large-scale disrupted and traumatic events that found similar stressor-strain relationships. Extra-organizational stressors defined as “environmental factors outside work

\(^2\)Fu et al. (2021) conducted a daily diary study. Wee and Fehr (2021) and Lin et al. (2021) conducted time-lagged field studies. D. Liu et al. (2021) and Hillebrandt and Barclay (2022) followed a two-study approach conducting time-lagged field studies and experiments.
that can lead to negative and potentially damaging reaction in individuals” (Byron & Peterson, 2002, p. 896) have been found to spill over into the workplace by influencing employees’ affective states (e.g., stress, burnout) as well as their work behavior (e.g., absenteeism, job satisfaction) (Bacharach & Bamberger, 2007; Bacharach et al., 2008; Byron & Peterson, 2002; Hochwarter et al., 2008; A. M. Ryan et al., 2003; Toker et al., 2015; Vinokur et al., 2011). Consequently, prior research, albeit limited, clearly suggests that the COVID-19 pandemic and extra-organizational stressors in general can spill over into the workplace by severely affecting employees. Thus, a central question appears to be which employees are most vulnerable to the distress caused by such extra-organizational stressors and how to protect them.

Research exploring boundary conditions in the COVID-19 context appears to have gained some traction (Hillebrandt & Barclay, 2022; Lin et al., 2021; Wee & Fehr, 2021), but is still considerably small. For this reason, Yuan et al. (2021) calls for more empirical research on critical contingencies that can protect employees’ work effectiveness from persistent health threats in the workplace as the COVID-19 pandemic unfolds. Furthermore, the limited number of studies that investigate boundary conditions in the COVID-19 context might not be as illuminating, since these studies rely primarily on between-person methodology (Lin et al., 2021; Shao et al., 2021; Wee & Fehr, 2021). However, within-person approaches might be more appropriate, since the threat posed by the pandemic tends to be perceived very differently (Al-Jayyousi et al., 2021). Even when taking a broader perspective on the research field, research on large-scale disruptive and traumatic events appears to have mainly focused on understanding employees’ strain reactions (Yuan et al., 2021), neglecting possible boundary conditions in the stressor-strain relationship. Therefore, James (2011, p. 933) emphasizes that an “improved understanding of how organizations can prepare for and respond to disaster […] is clearly needed to enhance their and their employees’ safety and success”. 
In summary, a small body of research has shown that the COVID-19 pandemic, and disruptive events in general, negatively affect employees. Although these studies contribute important insights into how extra-organizational stressors, such as the COVID-19 pandemic, spill over into the workplace, they fall short in identifying critical contingencies that either predispose employees to or protect employees from the distress caused by extra-organizational stressors.

1.2.3 Consequences of Telecommuting

When assessing the impact of telecommuting on employees, research often speaks of a “telecommuting paradox of mutually incompatible consequences for employees” (Gajendran & Harrison, 2007, p. 1526). Research has shown that telecommuting benefits employees in many ways, but the literature also indicates that telecommuting presents employees with a variety of challenges.

On the positive side, telecommuting has been found to provide employees with greater psychological control or autonomy by having a choice over the location, schedule (at least for some), and the means of work (Gajendran & Harrison, 2007; Gajendran et al., 2015). Perceived autonomy has particularly been highlighted as one of the principal mechanisms through which telecommuting benefits employees (Gajendran & Harrison, 2007). Furthermore, telecommuting appears to positively influence employees’ work performance (Gajendran & Harrison, 2007; Gajendran et al., 2015; Golden & Gajendran, 2019; Martin & MacDonnell, 2012) and organizational commitment (Golden, 2006a; Martin & MacDonnell, 2012), while reducing their emotional exhaustion (Golden, 2006a; Sardeshmukh et al., 2012), work-to-family conflict (Golden et al., 2006), and turnover intentions (Gajendran & Harrison, 2007; Golden, 2006a; Martin & MacDonnell, 2012).

On the negative side, many disadvantages of telecommuting appear to be linked to the fact that all interactions of telecommuters with organi-
zational members are, by definition, mediated by technology (T. D. Allen et al., 2015). Telecommuters appear to be more susceptible to stress and exhaustion resulting from the intensive use of technologies (i.e., technostress) (Camacho & Barrios, 2022). Moreover, telecommuters appear to face the risk of relational impoverishment at work as telecommuters have fewer face-to-face interactions, less rich communication, and ultimately a diminished social presence at work (Gajendran & Harrison, 2007). Research has shown that telecommuters tend to experience social and professional isolation (Bailery & Kurland, 2002; Kurland & Cooper, 2002) and could have poorer relationships with their coworkers (Gajendran & Harrison, 2007; Golden, 2007).

These mixed results show that the study of telecommuting requires more attention and that its effects are not fully understood. In attempting to clarify these discrepant results, research has started to shift the focus from the cross-sectional or between-person approach that has characterized the majority of telecommuting literature to the within-person methodology aiming to explore intraindividual differences across occasions (Vega et al., 2015). Relationships at the within-person level may be different in magnitude or even direction than findings at the between-person level (Curran & Bauer, 2011; Hoffman & Stawski, 2009; Zhang & Wang, 2014). Examining telecommuting at both levels of analysis is, therefore, necessary for a comprehensive understanding of the phenomenon.

Research at the within-person level indicates that the day-to-day phenomenological experience of working at home (or at another location away from the office) versus working at the office is a positive one. In particular, when telecommuting compared to working in the office employees appear to have higher levels of job performance (Delanoeije & Verbruggen, 2020; Vega et al., 2015), work engagement (Delanoeije & Verbruggen, 2020), job satisfaction (Vega et al., 2015), and job-related positive affective well-being (Anderson et al., 2015). Furthermore, employees’ ability to concentrate appears to be higher and their need for recovery appears to be lower.
on home days than on office days (Biron & van Veldhoven, 2016).

Although this strand of research provides valuable insights into the consequences of telecommuting from a within-person perspective, this literature has some limitations that might limit its explanatory power. First, previous research appears to have exclusively focused on employees’ experience of telecommuting versus working at the office, thus neglecting to provide theory on and empirical testing of hybrid work practices that center on the process of moving between work locations. Second, previous within-person research measured telecommuting nearly always by asking participants to place themselves in one set of categories each day (i.e., working at the office or working at home). Yet this dichotomous measurement approach may not be able to explain nuances in the variance of telecommuting and therefore may not provide a realistic assessment of how telecommuting is applied which ties into the lack of research on hybrid work practices. For this reason, Golden and Gajendran (2019) advocate measuring telecommuting by asking employees to indicate the extent to which they spent telecommuting in a given week. Lastly, the time span over which data were collected is relatively short ranging from five days (Vega et al., 2015) to two weeks (Anderson et al., 2015; Delanoeije & Verbruggen, 2020) and three weeks (Biron & van Veldhoven, 2016). Thus, prior research at the within-person level is only indicative for the short-term effects of telecommuting, neglecting possible long-term effects.

Taken together, the consequences of telecommuting for employees are not fully understood. Between-person research reveals both positive and negative effects of telecommuting on employees, emphasizing the importance of within-person methodology to advance our understanding of the telecommuting phenomenon. Extant within-person research suggests that telecommuting is beneficial to employees. However, within-person studies appear to lack theory specifying the impact of hybrid work practices

---

3One exception is Andel et al. (2021) who conducted a weekly diary study on loneliness and self-compassion in a telecommuting context.
and seem to have some methodological limitations that make it difficult
to draw valid conclusions about the long-term within-person impact of
telecommuting.

1.2.4 Research Gaps and Research Questions

Overall, an impressive amount of research has been conducted to ex-

plore employees’ adjustment to the organizational change driven by the
digitalization, the COVID-19 pandemic, and the flexibilization of the loca-
tion of work in the form of telecommuting. Nonetheless, research findings
remain fragmented and inconsistent across all three strands of literature.
Based on the literature review structured around the three workplace
dynamics presented in the previous sections, three research gaps are iden-
tified leading to three major research questions.

Research on the digitalization has studied the dark side and the bright
side of technology use. A central theme in this research appears to be
employees’ appraisal of the technology-related conditions and the intrap-
ersonal process through which employees decide how to respond either
positively or negatively to the appraised demands. In this vein, digital
competence has been repeatedly identified as a relevant boundary con-
dition to cope with the changing demands in a digitalized work setting.
However, the literature on digital competencies appears to have profound
conceptual and methodological limitations, leaving it unclear what digital
competence really is and how it can be measured. Accordingly, the first
research question is:

Research Question 1: What competence enables employees to effectively
perform in a digitalized work environment?

A small body of research clearly suggests that the COVID-19 pan-
demic can spill over into the workplace by severely affecting employees
raising the question of which employees are most vulnerable to the dis-
tress caused by the COVID-19 pandemic and how to protect them. How-
ever, research exploring boundary conditions in the COVID-19 context is
limited and further relies primarily on between-person research, although within-person approaches might be more appropriate given the fact that the threat posed by the pandemic tends to be perceived very differently. Thus, my second research question is:

Research Question 2: What factors either predispose employees to or protect employees from psychological distress caused the daily surge of local COVID-19 cases?

Research appears to struggle with conflicting effects of telecommuting on employees. Researchers have thus suggested that a within-person approach that studies the impact of telecommuting on individual-level employee outcomes over time might provide more accurate insights into the phenomenon and thereby contribute to clarifying the discrepancy in telecommuting research. Yet within-person studies seem to lack theory specifying the impact of hybrid work practices and appear to have some methodological limitations that make it difficult to draw valid conclusions about the long-term impact of telecommuting. Thus, my third research question is as follows:

Research Question 3: Does employees’ weekly effectiveness, as reflected in their weekly work performance and weekly emotional exhaustion, waxes and wanes in response to employees’ extent of telecommuting during a workweek over time?

1.3 Dissertation Outline and Chapter Structure

Taken together, this dissertation aims to advance our understanding of employees’ adaptive capacity in times of exponential, organizational change by taking an integrative approach and jointly investigating employees’ adaption to the digitalization, the COVID-19 pandemic and the flexibilization of the location of work in the form of telecommuting. Each of the following three chapters is devoted to one of the workplace dynamics to answer the research questions proposed in the previous chapter.
Chapter 2 addresses Research Question 1 inquiring about the true nature of digital competence. In Study 1, my co-author, Florian Kunze, and I draw on Campbell et al.’s (1993) performance model to conceptualize and empirically test a new competence — digital fluency. We propose digital fluency which consists of digital knowledge and digital self-efficacy to have a positive impact on employees’ digital work performance. Moreover, we build on social learning theory (Bandura, 1977) to suggest that leaders’ and coworkers’ digital fluency may play an enhancing role in this context. To test the theoretical model, we first draw on a time-lagged sample through Amazon’s Mechanical Turk to develop and validate a new scale to measure digital fluency. We then cross-validate the new scale and test the hypothesized model in a multi-source and time-lagged sample of 218 employees and 17 leaders of a medium-sized German technology company.

Chapter 3 deals with Research Question 2 inquiring about factors either predispose employees to or protect employees from psychological distress caused the COVID-19 pandemic. Applying the conservation of resources (COR) theory (Hobfoll, 1988, 1989), I argue that surging COVID-19 cases have the potential to be psychologically and physically draining and, thus, positively affect employees’ emotional exhaustion. Furthermore, I assume that employees’ age and extent of working from home are key context factors that influence employees’ strain reaction to the daily COVID-19 surge. I test the proposed relationships based on an eight-day diary study with largely a representative data set of the German workforce with 389 participants, which was integrated with official COVID-19 case statistics on the county level.

Chapter 4 addresses Research Question 3 inquiring about the within-person effect of the weekly extent of telecommuting on employees’ weekly effectiveness, as reflected in their work performance and emotional exhaustion, over time. Applying the conceptual framework of COR theory (Hobfoll, 1988, 1989), I suggest that the within-person effect of the weekly extent of telecommuting on employee effectiveness is curvilinear. More
specifically, I propose the effect to be u-shaped for the relationship between the extent of telecommuting and work performance and inversely u-shaped for the relationship between the extent of telecommuting and emotional exhaustion. I further explore the moderating role of self-goal setting in these relationships. To test my theoretical model, I draw on a dataset of 368 German employees tracked over 1.5 years.

While this dissertation focused on the three studies in Chapters 2 to 4, I attempt to interconnect them throughout the whole dissertation. In the introductory chapter, I present the digitalization, the COVID-19 pandemic and telecommuting as reinforcing, intertwined workplace dynamics that challenge employees to adapt to exponential, organizational change. Moreover, in a concluding chapter, I summarize the research findings from the three studies and discuss overall theoretical implications and avenues for future research as well as implications for managing employees’ adaptive responses to the current workplace transformation. The chapter structure of the dissertation is graphically summarized in Figure 1.1.
1.3. DISSERTATION OUTLINE AND CHAPTER STRUCTURE

**Figure 1.1:** Overview of Dissertation Structure

<table>
<thead>
<tr>
<th>Chapter 1</th>
<th>General Introduction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>- Relevance and Research Purpose</td>
</tr>
<tr>
<td></td>
<td>- Literature Review, Research Gaps, and Research Questions</td>
</tr>
<tr>
<td></td>
<td>- Overview of Dissertation Structure</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Chapter 2</th>
<th>Study 1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Digital Fluency – A Key Employee Resource to Perform in the Digital Age?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Chapter 3</th>
<th>Study 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Local COVID-19 Infections and Daily Employee Exhaustion: A Diary Study of Moderating Factors</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Chapter 4</th>
<th>Study 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>New Normal, but Good Normal? Testing the Effect of a Hybrid Way of Working on Employee Effectiveness</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Chapter 5</th>
<th>General Discussion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>- Summary and Integration of Study Findings</td>
</tr>
<tr>
<td></td>
<td>- Limitations and Avenues for Future Research</td>
</tr>
<tr>
<td></td>
<td>- Practical Implications</td>
</tr>
<tr>
<td></td>
<td>- Concluding Remarks</td>
</tr>
</tbody>
</table>
Digital Fluency – A Key Employee Resource to Perform in the Digital Age?

Sophia Zimmermann and Florian Kunze

Abstract

The ambivalent nature of digital technologies makes it necessary for organizations to promote and exploit factors that enable digital work performance. However, empirical research on competencies that predispose employees to succeed in a digitalized work environment appears to be limited. We address this research gap by conceptualizing and testing a competence that enables employees to effectively perform digitalized work environment: digital fluency. Drawing on Campbell et al.’s (1993) performance model, we propose that employees’ digital fluency, which consists of digital knowledge and digital self-efficacy, positively affects employees’ digital work performance. We further build on social learning theory to argue that leaders’ and coworkers’ digital fluency moderates the relationship between employees’ digital fluency and their digital work performance. We find support for the positive effect of employees’ digital fluency on their digital work performance and the moderating effect of leaders’ digital flu-
ency in a multi-source and time-lagged sample of 218 employees and 17 leaders from a medium-sized German technology company.

*Keywords:* digital fluency; digital knowledge; digital self-efficacy; digital work performance
2.1 Introduction

The transformative power of digitalization involves opportunities and major challenges for organizations (Day et al., 2010). On the positive side, working with digital technologies can enhance work performance by providing employees with the autonomy to pick and choose where and when to work, creating a work structure that suits their needs (Gajendran & Harrison, 2007). On the negative side, however, digital technology can hinder performance as employees might perceive losing control over their time and space as they are constantly connected due to the pervasiveness of digital technologies (Büchler et al., 2020). Hence, working with digital technologies appears to blur the boundaries between work and private life (Boswell & Olson-Buchanan, 2007) and further create feelings of being stressed out, a condition known as technostress (Srivastava et al., 2015; Tarafdar et al., 2015). Consequently, working with digital technologies is a double-edged sword with the potential for having opposite effects on employee performance.

Notwithstanding their paradox nature (Mazmanian et al., 2013; van Zoonen & Rice, 2017), digital technologies have become crucial in most occupations across industries as modern work settings are characterized by technological achievements, such as artificial intelligence, big data, augmented reality or robotization (Díaz Andrade et al., 2019). Consequently, successfully applying these technologies for digital work performance appears to be key for business success in the future workplace. Drawing on work performance theory (Cummings & Schwab, 1973), we define digital work performance as the appropriate application of digital technologies necessary to accomplish expected, specified, or formal role requirements on the part of organizational members. Despite the ambiguity of working with digital technologies, employees who exhibit digital work performance can exploit digital technologies and, thus, ultimately deliver work outcomes.
The importance of digital work performance raises the question of which qualities predispose employees to perform in a digitalized work environment successfully. A recent review (Oberländer et al., 2020) shows that several frameworks and concepts are already proposed in the literature to describe digital competencies (e.g., Ala-Mutka, 2011; Ferrari, 2012; Hatlevik, 2009; Mengual-Andrés et al., 2016). At the same time, the review reveals profound conceptual and methodological limitations of the digital competencies literature. In terms of conceptualization, frameworks appear to considerably differ in content, scope and terminology since they vary in the number of dimensions and basic assumptions of digital competence and the labels used to describe it. As Oberländer et al. (2020, p. 4) point out, the literature appears not only to be in “disagreement on the terminology for the same construct, but also on the structure of the concept behind the same term”. Considering empirical evidence, Oberländer et al. (2020, p. 5) highlight the documentation of the data collection, instruments used, and data analysis of most publications as “insufficient”. Furthermore, the digital competencies of workers, which is the main interest of this paper, appears to have rarely been subject to empirical investigation. Therefore, Oberländer et al. (2020, p. 5) “conclude that more scientific methods and rigorous scientific practice are needed to address DC [digital competence] at work”. They particularly encourage industrial and organizational psychologists to address this research gap.

Following this call, our paper aims to conceptualize and empirically test an individual competence – digital fluency – that effectively enables employees to perform in a digitalized work environment. Drawing on Campbell et al.’s (1993) performance model, we posit that one integral component of digital fluency is digital knowledge which implies knowing what to do and how to do it when working with digital technologies. However, beyond digital knowledge, employees need to be willing to use digital technologies to exhibit digital work performance ultimately. In line with this argumentation, increasing evidence in the information systems literature shows the importance of efficacy beliefs in determining individual
behavior toward and performance using information technology (Agarwal et al., 2000; Downey & Rainer, 2009; Teo, 2009; Wilfong, 2006). Therefore, we conceptualize digital self-efficacy, a person’s inner belief in their capability to successfully exploit digital technologies to deliver work outcomes, as second integral component of digital fluency.

Endowed with the combination of high digital knowledge and digital self-efficacy, digitally fluent employees are proposed to exhibit digital work performance. Furthermore, building on social learning theory (Bandura, 1977), we argue that the level of digital fluency in employees’ direct work environment will function as a performance enabler in the workplace. Hence, we propose that digitally fluent employees show enhanced digital work performance when their leader, as well as their coworkers, are digitally fluent as well. Our conceptual model is illustrated in Figure 2.1.

In explaining digital work performance, we contribute to the existing research on the digitalization of the workplace in several ways. First, we build a theory regarding the emergence of digital work performance. We conceptualize digital fluency as a new positive facet necessary for employees’ digital work performance by integrating the theory of work performance (Campbell et al., 1993) with the digital workplace literature (Agarwal et al., 2000; Downey & Rainer, 2009; Teo, 2009; Wilfong, 2006). We further extend this theoretical perspective by considering potential enablers of digital performance, such as leaders’ and coworkers’ digital fluency, based on arguments from social learning theory (Bandura, 1977). Second, we follow the call by Oberländer et al. (2020) for more rigorous scientific research on digital competencies at work from the industrial-organizational psychology field. Responding to this call we provide a theoretical conceptualization and a validated quantitative measure of digital fluency. Additionally, we consider digital fluency in a work setting — a context that has largely been neglected by prior research (Oberländer et al., 2020). Therefore, our research contributes to clarifying the concept of digital competencies at work. Third, our development and testing
of theory regarding the emergence of digital work performance provide a possible point of practical intervention for executives and companies: if factors shaping digital work performance are identified, interventions to support change in these factors can be put in place. We thereby help organizations and employees to exploit the benefits of digitalization, while overcoming its challenges. In summary, our research is a significant step forward in explaining and facilitating digital work performance in the current and future workplace.

![Conceptual Model Study 1](image)

**Figure 2.1:** Conceptual Model Study 1

### 2.2 Theory Development

Employees differ considerably in their job performance level. To explain these differences, a large body of literature focused on person-specific variables (i.e., variables that differ between individuals) as predictors of job performance (Sonnentag et al., 2008). Most research on person-specific predictors of job performance focused on cognitive abilities, knowledge, experience, and non-cognitive traits (Sonnentag et al., 2008).

In this vein, Campbell et al.’s (1993) seminal performance model proposes declarative and procedural knowledge as core individual performance determinants. Declarative knowledge captures the knowledge of facts, rules, principles, procedures (i.e., knowing what to do), while procedural knowledge is the “capability attained when declarative knowledge [...] has been successfully combined with knowing how and being able to
perform a task” (McCloy et al., 1994, p. 494). Furthermore, the authors emphasize that to perform a task, beyond knowledge and skills, a person must “actually choose to work on the job tasks for some time at some level of effort” (McCloy et al., 1994, p. 494). Transferring these arguments to the context of digital work performance, we assume that, to exhibit digital work performance, employees first and foremost need to know what to do when using digital technologies and how to do it. Furthermore, employees need to be inclined to use digital technologies to fulfill their role requirements adequately.

Considering the willingness to use digital technologies, the information systems literature provides several models of technology acceptance and use: the technology acceptance model (Davis, 1989), the theory of reasoned action (Ajzen & Fishbein, 1980), and the theory of planned behavior (Ajzen & Madden, 1986; Mathieson, 1991). Although these models consider different relationships, they all emphasize that individual beliefs or perceptions about and attributes toward new information technology are highly salient determinants of usage behavior (Agarwal et al., 2000). In particular, more recent research in technology acceptance highlights the importance of efficacy beliefs in determining individual behavior toward and performance using information technology (Agarwal et al., 2000; Downey & Rainer, 2009; Teo, 2009; Wilfong, 2006).

2.2.1 Digital Fluency

Building on the arguments proposed by Campbell et al.’s (1993) performance model and the evidence in the information systems literature highlighting the importance of efficacy beliefs in digital work performance (Agarwal et al., 2000; Teo, 2009), we argue that employees need to be both knowledgeable and self-confident when using digital technologies to exhibit digital work performance. Aiming to capture this duality in predicting digital work performance, we introduce a new higher-order construct — digital fluency — that combines high levels of both digital knowledge
and digital self-efficacy.

Regarding the first component of digital fluency, we follow Campbell et al.’s (1993) approach to performance-relevant knowledge and define digital knowledge as the technical expertise and fundamental understanding of the scope and applicability of digital technologies. Digitally knowledgeable employees know with effortless ease what to do and how to do it when dealing with digital technologies (Briggs et al., 2012). For example, they can navigate ever-changing apps and programs or operate digital devices with ease. Furthermore, digitally knowledgeable employees use digital technologies on purpose, as they develop an understanding of when and why digital technologies add value (Briggs et al., 2012). For instance, digitally knowledgeable employees might refuse to work with digital technologies at the beginning of a project, preferring to work with analog tools and face-to-face as trust and norms among team members still need to be established. When the project is more advanced, they may revert to digital communication to increase efficiency by working remotely.

Regarding the second component of digital fluency, we propose digital self-efficacy to capture employees’ inner confidence in their ability to fulfill their role requirements through digital technologies and, thus, deliver work outcomes. Digital self-efficacy is rooted in the broader concept of self-efficacy, but follows Bandura’s (1997) recommendation that self-efficacy measures should reflect a particular context domain of functioning rather than global functioning. In defining digital self-efficacy, we further considered the dimensions of self-efficacy judgments (Compeau & Higgins, 1995): magnitude, strength, and generalizability. Employees with high levels of digital self-efficacy perceive themselves as fulfilling more difficult role requirements with digital technologies relying on less

---

By adopting the proposed definition of digital self-efficacy, we go beyond the scope of related constructs, such as computer self-efficacy, which is often studied in the literature (Compeau & Higgins, 1995; Wilfong, 2006). Defined as a “judgement of one’s capability to use a computer” (Compeau & Higgins, 1995, p. 192), computer self-efficacy is generally concerned with the accomplishment of computing tasks and the operation of different software packages and computer systems. Digital self-efficacy is not bound to a specific type of technology, but rather focused on the application of all kinds of digital technologies (e.g., computers, smartphones, iPads, virtual reality, robots) necessary for the fulfillment of employees’ work roles.
support and assistance (magnitude). They are further likely to display greater confidence when dealing with digital technologies to perform work even in times of difficulty (strength). Lastly, employees with high levels of digital technology welcome any digital technology (e.g., computers, smartphones, tablets, virtual reality, robots) that helps them to improve their work performance (generalizability). Therefore, high levels of digital self-efficacy determine how employees think, behave, and react in self-enhancing ways when dealing with digital technologies to perform at work (Bandura, 1982). For example, sales employees with high levels of digital self-efficacy are likely to perceive virtual reality technology as an opportunity to reach a greater audience for their products with less effort. In contrast, sales employees with lower levels of digital self-efficacy may perceive virtual reality as a threat to their established work routines.

2.2.2 Digital Fluency: a Determinant of Digital Work Performance

Digital fluency — the combination of digital knowledge and digital self-efficacy — is proposed to be a person-specific predictor that explains differences in digital work performance. Endowed with high levels of both digital knowledge and digital self-efficacy, digitally fluent employees are argued to exhibit greater digital work performance than to employees with low levels of digital fluency.

Digitally fluent employees are familiar with the general technical use of digital technologies and know when and why a digital or an analog approach is a more viable solution (Briggs et al., 2012). Thus, they can choose and pursue the most suitable approach towards fulfilling work-related tasks in a digitalized work environment. Furthermore, digitally fluent employees have an empowering inner mindset that drives them to apply their digital knowledge to meet their role requirements and sustain efforts to overcome potential difficulties (Bandura, 1982). They are convinced of their ability to deliver work outcomes in a digitalized work
setting perceiving digital technologies as assets for even better performance.

In contrast, employees with low levels of digital fluency deploy their attention and efforts so that it impairs digital work performance. Without sufficient levels of digital fluency, employees may lack the necessary knowledge and regard themselves as inefficacious in coping with digital demands (Bandura, 1982). Hence, they might feel reluctant to take on digital technology-related tasks or fail to fulfill them. Moreover, employees are likely to focus on their deficiencies regarding digital competencies and imagine that potential difficulties are more severe than they really are (Lazarus & Launier, 1978). Consequently, employees might divert their attention from the best-performance approach to concerns over failings and mishaps (Bandura, 1982). In conclusion, we propose digital fluency to be a person-specific predictor of digital work performance leading to the following hypothesis:

_Hypothesis 1: Employees’ digital fluency has a positive effect on employees’ digital work performance._

### 2.2.3 Leaders’ and Coworkers’ Digital Fluency: Potential Contextual Factors in Explaining Digital Work Performance

Social learning theory (Bandura, 1977) lends an important theoretical lens to further advance our knowledge of the relationship between digital fluency and digital work performance. According to this framework, individuals learn “through the influence of example” (Bandura, 1977, p. 5). Employees observe the behaviors demonstrated by role models and thereby engage in learning processes. Among the potential models to choose from, attractive models capture employees’ attention. Attractiveness is based on several characteristics, such as competence and success (Weiss, 1977, 1978) as well as status (Lefkowitz et al., 1955), and power (Bandura et al., 1963; Lippitt et al., 1952). Furthermore, Bandura highlights that especially competence of the change source is paramount if
attempts to alter another person’s behavior are to be successful.

Building on these basic tenets of social learning theory (Bandura, 1977), we assume that employees can sustainably enhance their digital work performance by observing role models which they perceive as competent in the digital realm. Digital fluency is, therefore, proposed to make individuals attractive role models in a digitalized work context. We focus on leaders and coworkers as two likely sources of behavioral change, since employees can best assess and observe the digital fluency level of their leaders and coworkers due to their intensive interaction at the workplace. Therefore, we propose the digital fluency level of leaders and coworkers to play a moderating role in the positive relationship between employees’ digital fluency and their digital work performance.

Digitally fluent leaders and coworkers are especially well-positioned for influencing the behavior of their followers by effective role modeling. Digitally fluent leaders and coworkers are proposed to demonstrate competence and attainable success in a digitalized work setting. Endowed with high levels of both digital knowledge and digital self-efficacy, digitally fluent leaders and coworkers are likely to be able to confidently demonstrate how to exploit digital technologies to deliver work outcomes. Therefore, employees may perceive their digitally fluent leaders and coworkers as credible sources of change and, thus, are more open for behavioral change attempts (F. A. Powell, 1965). Consequently, through learning from digitally fluent leaders and coworkers, employees can deepen their digital knowledge and gain a better understanding of what to do and how to do it when delivering work outcomes with the help of digital technologies. In doing so, they might become more confident in their capacity to use digital technologies to fulfill their role requirements and engage in enhanced digital work performance behaviors. A vast body of empirical literature substantiates the crucial role of leaders and coworkers in driving employees’ work performance (Chiaburu & Harrison, 2008; Parker et al., 2017).
In contrast, leaders and coworkers with low levels of digital fluency may not provide attractive examples of successful behavior in a digitalized work environment. Due to the lack of digital knowledge and digital self-efficacy, leaders and coworkers with low levels of digital fluency might not demonstrate competence in the digital realm. Hence, they may not want to draw employees’ attention to their lacking digital skills and potentially low levels of digital work performance. As a result, leaders and coworkers with low levels of digital fluency might not be perceived as models worthy of imitation. Therefore, employees cannot enhance their digital fluency and, thus, digital work performance by engaging in behavioral modeling of leaders and coworkers with low levels of digital fluency.

In summary, we argue that employees can expand their digital knowledge and self-efficacy to achieve enhanced digital work performance by observing digitally fluent leaders and coworkers leading to the following hypotheses:

**Hypothesis 2**: Leaders’ digital fluency moderates the positive relationship between employees’ digital fluency and their digital work performance such that the effect of employees’ digital fluency on their digital work performance is stronger if the leader’s digital fluency is high.

**Hypothesis 3**: Coworkers’ digital fluency moderates the positive relationship between employees’ digital fluency and their digital work performance such that the effect of employees’ digital fluency on their digital work performance is stronger if the digital fluency of coworkers is high.

### 2.3 Methods and Results

In the following, we will proceed in two steps to empirically test our hypothesized relationships. In Study 1, we will develop and validate a new scale to measure digital fluency. Subsequently, in Study 2, we will further cross-validate the new scale in an additional sample and test the hypothesized model.
2.3. METHODS AND RESULTS

2.3.1 Study 1

2.3.1.1 Digital Fluency Scale Development

We developed a six-item scale based on our conceptualization of digital fluency. In line with our theoretical argument, we defined digital fluency as a second-order construct composed of two first-order constructs — digital knowledge and digital self-efficacy.

To develop a measure to assess digital knowledge, we transferred Campbell et al.’s (1993) approach to performance-relevant knowledge (i.e., knowing what to do and how to do it) to a digital context. Moreover, we assume that beyond knowing what to do and how to do it when dealing with digital technologies, employees need to know when the use of digital technologies adds value to be able to find the most viable approach (i.e., digital versus analog) to fulfilling one’s role requirements. We, therefore, developed three manifest indicator items to capture digital knowledge. The exact wording of the items is displayed in Table 2.1. The phrase “without having to think about it” was added to indicate proficiency and intuition in using digital technologies. All items were assessed on a five-point scale ranging from 1 (strongly disagree) to 5 (strongly agree).

The three-item scale measuring digital self-efficacy was developed to capture respondents’ confidence in using digital technologies to add value in the work context. We used a five-point Likert-type measurement format ranging from 1 (strongly disagree) to 5 (strongly agree), which is recommended as an equivalent alternative to the traditional format, which requires participants to assess both the magnitude and strength of self-efficacy (Maurer & Pierce, 1998). Table 2.1 shows the exact wording of the items.
Table 2.1: The Exact Wording of the Digital Fluency Scale

<table>
<thead>
<tr>
<th>#</th>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DF</td>
<td>Digital fluency</td>
<td></td>
</tr>
<tr>
<td>DK</td>
<td>Digital knowledge</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>DK01</td>
<td>I know how to use digital technologies without having to think about it.</td>
</tr>
<tr>
<td>2</td>
<td>DK02</td>
<td>I know what to do when using digital technologies without having to think about it.</td>
</tr>
<tr>
<td>3</td>
<td>DK03</td>
<td>I know when it makes sense to work with digital technologies without having to think about it.</td>
</tr>
<tr>
<td>DSE</td>
<td>Digital self-efficacy</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>DSE01</td>
<td>I am confident that I can use digital technologies to improve my job performance.</td>
</tr>
<tr>
<td>2</td>
<td>DSE02</td>
<td>I am confident that I can reliably achieve the desired work results with the help of digital technologies.</td>
</tr>
<tr>
<td>3</td>
<td>DSE03</td>
<td>All in all, I am confident regarding my digital skills.</td>
</tr>
</tbody>
</table>

2.3.1.2 Data Collection and Sample

We collected a two-days time-lagged sample through Amazon’s Mechanical Turk (MTurk), an Internet marketplace where scholars can post online studies for paid workers (MTurkers) (Casler et al., 2013). MTurk provides distinct benefits compared with research conducted using more traditional samples: (1) a large and diverse participant pool, (2) increased work experience over other subject pools, such as students, and (3) a broad distribution across the labor market (Aguinis et al., 2021; Behrend et al., 2011; Berinsky et al., 2012), allowing for greater external validity than study samples coming from individual labor sectors or companies.

In line with previous recommendations (Aguinis et al., 2021), we took several measures to ensure the data quality of our MTurk sample. First, we only recruited participants who had completed 50 or more HITS (“human intelligence tasks”) with a high ratio (95 percent) of approved-versus-submitted tasks (Hauser & Schwarz, 2016; Litman et al., 2015). Studies have shown that MTurkers with a high reputation are more attentive in online tasks, since they are reluctant to lose their high reputation and,
thus, their access to desirable tasks by failing to gain approval for submitted tasks (Peer et al., 2014). Second, we reduced perceived researcher unfairness and MTurker inattention by using two attention checks (i.e., instructed items that direct MTurkers to choose a specific option) and a consent form to describe data protection measures and compensation rules (i.e., participants who failed at least one attention check were not compensated). Third, we paid more than U.S. minimum wage, that is $2.37 for the first part and $1.00 for the second part of our study. We approved compensation for completed responses within 24 hours and specified the reason for rejecting compensation.

We restricted our sample to U.S. employees and business owners, since we aimed to investigate digital fluency in a work context. In T1, 201 MTurkers completed the questionnaire, while 167 of those also participated in T2. We screened the data using responses to the attention checks, consistency in terms of gender and age from T1 to T2 and relative speed index values\(^2\). The final sample consisted of 129 participants in T1 and 101 participants in T2. The age of the respondents ranged from 23 to 71 years, with an average of 40 years (SD = 10.20). More men (58.10 percent) than women (41.90 percent) participated in the study.

Besides digital fluency, we collected data on several constructs for discriminant and predictive validity checks. Detailed information on the measures (i.e., exact wording of the items, response format, reliability estimates, results of confirmatory factor analyses (CFA)) is provided in the appendix in chapter A.

---
\(^2\)The relative speed index is a completion time indicator which is standardized by the sample completion time median and controls for single outliers regarding page completion times. Leiner (2019) recommends the use of the relative speed index to identify low data quality in Internet surveys. Participants were excluded whose relative speed index was above 1.3 in at least one of the surveys (Leiner, 2019).
2.3.1.3 Results

2.3.1.3.1 Internal Validity

We examined the internal consistency of the digital fluency scale at T1 using SPSS statistics 27 and Amos 27 Graphics. Table 2.2 shows the results of the internal consistency checks together with the descriptive statistics of the digital fluency scale. The item-total correlations for all items were above 0.63 for each subscale, showing strong relationships between items and their respective scales. Alpha reliabilities as well as omega values for digital fluency and its subscales were all above the recommended minimum of 0.70 (Dunn et al., 2014). The composite reliability (CR) and the average variance extracted (AVE) for each subscale can be considered acceptable, as the CR is greater than 0.70, and the AVE is greater than 0.50 (Bagozzi & Youjae, 1988). We, therefore, concluded that the digital fluency scale is internally consistent.

Thereafter, we performed an exploratory factor (EFA) analysis and a CFA to assess the internal structure of our digital fluency measure (Goodwin, 1999). In line with our theoretical conceptualization, the EFA yielded a two-factor solution. The first factor had an eigenvalue of 3.43 and explained 57.24 percent of the variance, while the second factor had an eigenvalue of 1.13 and explained 18.91 percent of the variance. The two-factor solution was further supported by the rotated factor matrix. The digital knowledge items loaded on average better on the first factor (0.85) than on the second factor (0.24), while the digital self-efficacy items loaded higher on the second factor (0.83) than on the first factor (0.22).

The results of the subsequent CFA further supported the second-order structure of the digital fluency measure. As displayed in Table 2.3, the overall model fit of a second-factor model where items loaded on their respective dimensions and each dimension loaded on a second-order latent digital fluency factor revealed superior results to a one-factor model, with all items loading on a common latent factor. In addition, all item loadings
were significant \((p < 0.001)\) and were all well above 0.50 — a threshold often applied in factor analysis to evaluate the fit of latent constructs to their respective indicators (Hulland, 1999).

**Table 2.2:** Descriptive Statistics and Internal Validity Estimates of the Digital Fluency Scale in the Mturk Sample (Study 1)

<table>
<thead>
<tr>
<th>#</th>
<th>Notation</th>
<th>M</th>
<th>SD</th>
<th>ITC</th>
<th>(\alpha)</th>
<th>(\omega)</th>
<th>CR</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DF</td>
<td>4.30</td>
<td>0.49</td>
<td>0.85</td>
<td>0.84</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>DK</td>
<td>4.26</td>
<td>0.57</td>
<td>0.86</td>
<td>0.86</td>
<td>0.89</td>
<td>0.72</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>DK01</td>
<td>4.26</td>
<td>0.61</td>
<td>0.79</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>DK02</td>
<td>4.26</td>
<td>0.66</td>
<td>0.76</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>DK03</td>
<td>4.25</td>
<td>0.67</td>
<td>0.64</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>DSE</td>
<td>4.34</td>
<td>0.57</td>
<td>0.82</td>
<td>0.82</td>
<td>0.87</td>
<td>0.68</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>DSE01</td>
<td>4.45</td>
<td>0.67</td>
<td>0.63</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>DSE02</td>
<td>4.31</td>
<td>0.66</td>
<td>0.71</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>DSE03</td>
<td>4.28</td>
<td>0.67</td>
<td>0.67</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* \(N = 129; M = \text{mean}; SD = \text{standard deviation}; ITC = \text{item-total correlation}; \alpha = \text{Cronbach's alpha}; \omega = \text{omega}; CR = \text{composite reliability}; AVE = \text{average variance extracted}.*

**Table 2.3:** CFA Results for Digital Fluency

<table>
<thead>
<tr>
<th>Model</th>
<th>(\chi^2)</th>
<th>df</th>
<th>(\chi^2/df)</th>
<th>(\Delta\chi^2)</th>
<th>(\Delta df)</th>
<th>CFI</th>
<th>IFI</th>
<th>TLI</th>
<th>SRMR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two-factor model</td>
<td>8.71</td>
<td>8</td>
<td>1.09</td>
<td></td>
<td></td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.03</td>
</tr>
<tr>
<td>One-factor model</td>
<td>66.94</td>
<td>9</td>
<td>7.44</td>
<td>58.23***</td>
<td>1</td>
<td>0.80</td>
<td>0.80</td>
<td>0.66</td>
<td>0.12</td>
</tr>
</tbody>
</table>

*Note.* \(N = 129; \chi^2 = \text{chi-square; df = degrees of freedom; CFI = comparative fit index; IFI = incremental fit index; TLI = Tucker-Lewis-Index; SRMR = standardized root mean square residual; *** p \leq 0.001.***

2.3.1.3.2 Discriminant Validity

We tested the discriminant validity of the digital fluency scale to related constructs — general self-efficacy (Chen et al., 2001), computer self-efficacy (Compeau & Higgins, 1995), resistance to change (Oreg, 2003), and locus of control (Levenson, 1973). These variables appeared relevant for a discriminatory check as general self-efficacy, and digital fluency
are both rooted in Bandura’s (1982) self-efficacy theory, computer self-efficacy is a similar construct to digital self-efficacy, the notion of digital capabilities may evoke feelings of resistance towards digital change, and employees might further perceive their successful performance to be the result of chance, fate, or powerful others, rather than their own capabilities.

Table 2.4 illustrates the results of the discriminant validity checks. For each construct (i.e., general self-efficacy, computer self-efficacy, resistance to change, locus of control), we first specified a two-factor model in which the respective items loaded on separate dimensions and then compared it to a one-factor solution, in which all items loaded on one joint dimension. Table 2.4 shows that for all comparison constructs, a two-factor solution resulted in a superior fit. The correlations between digital fluency and general self-efficacy, computer-self-efficacy, resistance to change as well as locus of control appeared to be small to moderate, but did not indicate an excessively strong relationship. Consequently, these results supported the discriminant validity of the digital fluency measure.

2.3.1.3.3 Predictive Validity

Furthermore, we inspected the relationship of the new digital fluency measures to relevant outcomes to establish a predictive validity (Lewis, 2003). Since we argue that digital fluency enables employees to perform in a digitalized work setting, we expect the digital fluency scale to be positively related to performance measures. All of the measures in the MTurk sample were self-reports, including the performance scales, but measured with a time-lag. We, therefore, computed correlation coefficients between digital fluency measured at T1 and digital productivity (Tarafdar et al., 2007), in-role performance (Williams & Anderson, 1991), and digital work performance measured at T2.

The results support the expected relationships as the digital fluency scale was positively related to digital productivity ($r = 0.60, p < 0.01$),
Table 2.4: Discriminant Validity of Digital Fluency in the MTurk Sample (Study 1)

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Correlation</th>
<th>Model</th>
<th>$\chi^2$</th>
<th>df</th>
<th>$\chi^2$/df</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta df$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital fluency vs. general self-efficacy</td>
<td>$r = 0.47^{**}$</td>
<td>two-factor-model</td>
<td>85.57</td>
<td>75</td>
<td>1.14</td>
<td>218.73***</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>one-factor model</td>
<td>304.29</td>
<td>77</td>
<td>3.95</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Digital fluency vs. computer self-efficacy</td>
<td>$r = 0.54^{**}$</td>
<td>two-factor-model</td>
<td>99.61</td>
<td>75</td>
<td>1.33</td>
<td>176.70***</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>one-factor model</td>
<td>276.31</td>
<td>77</td>
<td>3.59</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Digital fluency vs. resistance to change</td>
<td>$r = -0.26^{**}$</td>
<td>two-factor-model</td>
<td>245.81</td>
<td>183</td>
<td>1.34</td>
<td>490.87***</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>one-factor model</td>
<td>736.67</td>
<td>189</td>
<td>3.90</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Digital fluency vs. locus of control</td>
<td>$r = -0.27^{**}$</td>
<td>two-factor-model</td>
<td>470.64</td>
<td>372</td>
<td>1.27</td>
<td>497.96***</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>one-factor model</td>
<td>968.60</td>
<td>377</td>
<td>2.57</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. N = 129; $\chi^2$ = chi-square; df = degrees of freedom; ** p $\leq$ 0.01; *** p $\leq$ 0.001.
in-role performance ($r = 0.46$, $p < 0.01$) and digital work performance ($r = 0.41$, $p < 0.01$). Furthermore, we regressed\(^3\) digital productivity, in-role performance, and digital work performance on digital fluency while controlling for age and gender. Digital fluency and all controls were $z$-standardized prior to the regression analysis (Frazier et al., 2004). The findings showed a significant positive effect of digital fluency on all outcomes (digital productivity: $\beta = 0.35$, $p < 0.001$, $R^2 = 0.36$; in-role performance: $\beta = 0.25$, $p < 0.001$, $R^2 = 0.19$; digital work performance: $\beta = 0.32$, $p < 0.05$, $R^2 = 0.17$). Consequently, the digital fluency scale appeared to be predictably valid as it correlates with theoretically relevant outcomes.

2.3.2 Study 2

2.3.2.1 Methods

2.3.2.1.1 Data Collection and Sample

We collected data from a German manufacturing company as part of an employee survey. The company seemed to be suited for the study as it experienced a digital transformation as indicated by the digitalization of work processes across diverse fields of activity. Production workers digitally operated manufacturing machines and tracked their progress in the manual assembly line by using iPads. Logistics employees used a picking app, and sales workers applied augmented reality to advise customers on products. As a result, employees across all divisions had been confronted with digital technologies and, thus, had gained experience in working with digital technologies at the time of data collection.

\(^3\)We additionally tested the predictive validity on the latent level using structural equation modeling. Digital fluency was significantly and positively related to all outcomes:  

- **Digital productivity**: $\beta = 0.82$, $p < 0.001$, $R^2 = 0.65$, $\chi^2 = 74.20$; $df = 49$; $\chi^2/df = 1.51$; CFI = 0.95; IFI = 0.95; TLI = 0.90; SRMR = 0.07.  
- **In-role performance**: $\beta = 0.71$, $p < 0.001$, $R^2 = 0.50$, $\chi^2 = 90.42$; $df = 60$; $\chi^2/df = 1.51$; CFI = 0.94; IFI = 0.94; TLI = 0.93; SRMR = 0.07.  
- **Digital work performance**: $\beta = 0.54$, $p < 0.001$, $R^2 = 0.29$, $\chi^2 = 21.87$; $df = 23$; $\chi^2/df = 0.95$; CFI = 1.00; IFI = 1.00; TLI = 1.01; SRMR = 0.05.
The employee survey was conducted in April 2018. All employees working for three months or longer in the company (n = 240) and their respective department heads (n = 17) located at the German headquarter were invited by the company’s management to participate in the employee survey. The communication informed the employees about the purpose of the survey and provided a personal identification code and a link to a web-based survey hosted by an independent third party. An e-mail reminder was sent after one week.

A total of 218 employees, representing a response rate of 91 percent, participated in the survey. The age of the respondents ranged from 18 to 66 years, with an average of 41 years (SD = 11.56). Furthermore, the respondents had been working for this company for ten years on average (SD = 8.66). Individual responses were more strongly represented by males (69.70 percent) and half of the respondents worked in production positions (50.00 percent), followed by sales (24.77 percent), innovation (13.76 percent), services (7.80 percent), and others (3.67 percent). Furthermore, all 17 department heads took part in the survey. The leaders were on average 42 years old (SD = 8.85), predominately male (76.47 percent), and had been associated with this company for seven years on average (SD = 7.09).

In addition, we also collected data from two other sources. First, we asked employees’ direct supervisors (i.e., department heads or team leaders) to rate their subordinates’ digital performance two months after the employee survey was completed. By applying this multi-source and time-lagged approach when collecting performance data, we were able to reduce the risk of common method variance (Podsakoff et al., 2003) influencing the relationship between digital fluency and digital work performance. We received the performance evaluation for 200 employees (91.74 percent response rate). Second, the Human Resources Department provided us with demographic data on age, gender, tenure, and the sickness rate of all employees who participated in the survey.
2.3.2.1.2 Measures

Unless otherwise noted, 5-point Likert-type scales (1 = disagree, 5 = agree) were used for all measures. All items were coded such that higher scores indicate higher levels of the construct.

2.3.2.1.2.1 Employees’ Digital Fluency  Employees’ digital fluency was assessed by using the six-item digital fluency scale developed in Study 1. The internal consistency estimates of digital fluency were $\alpha = 0.92$ and $\omega = 0.92$ (digital knowledge: $\alpha = 0.94$, $\omega = 0.94$; digital: self-efficacy $\alpha = 0.93$, $\omega = 0.93$), exceeding the minimum threshold of 0.70 (Nunnally, 1978). Furthermore, the results of the subsequent CFA reaffirmed the second-order structure of the digital fluency measure. The overall model fit of a second-factor model revealed superior results to a one-factor model (two-factor model: $\chi^2 = 45.86; df = 8; \chi^2/df = 5.73; CFI = 0.97; IFI = 0.97; TLI = 0.94; SRMR = 0.06$; one-factor model: $\chi^2 = 402.75; df = 9; \chi^2/df = 44.75; \Delta \chi^2 = 356.89^{***}; \Delta df = 1; CFI = 0.69; IFI = 0.69; TLI = 0.48; SRMR = 0.16$).

2.3.2.1.2.2 Leaders’ Digital Fluency  Information on the digital fluency level of the 17 leaders was obtained by using the six-item digital fluency scale from Study 1. The internal consistency estimate of leaders’ digital fluency was acceptable ($\alpha = 0.92; \omega = 0.93$; digital knowledge: $\alpha = 0.88$, $\omega = 0.92$; digital self-efficacy: $\alpha = 0.97$, $\omega = 0.97$).

2.3.2.1.2.3 Coworkers’ Digital Fluency  Coworkers’ digital fluency was measured by using the six-item digital fluency scale from Study 1. We averaged the scores of the coworkers within a team per item (excluding own scores) and subsequently took the average of all items to build the new variable “coworkers’ digital fluency”. The internal consistency estimate of coworkers’ digital fluency was acceptable ($\alpha = 0.97$, $\omega = 0.98$; digital knowledge: $\alpha = 0.98$, $\omega = 0.98$; digital self-efficacy: $\alpha = 0.97$, $\omega = 0.97$).
Internal agreement of the team members was shown through $r_{wg}$ measure of 0.99, well above the commonly applied cut-off of 0.70 (LeBreton & Senter, 2008).

### 2.3.2.1.2.4 Digital Work Performance
We measure digital work performance using one item to limit the amount of time each supervisor had to assess their numerous employees and hence to achieve valuable and reliable answers. The item was “How often has [employee’s name] reliably achieved desired work results with the help of digital technologies within the last six months?” The item was rated by the respective direct supervisor of each employee on a seven-point scale ranging from 1 (never) to 7 (always). The direct supervisor was either the department head or the team leader, depending to whom the employee directly reported.

### 2.3.2.1.2.5 Controls
We selected controls based on a sound theoretical foundation and prior empirical evidence. Therefore, gender, age, department affiliation, employees’ autonomy, task-related and environmental strain and employees’ sickness rate were included as controls. Controlling for gender, age, and department affiliation appeared necessary as the competence to exhibit digital work performance might vary depending on these factors. It is conceivable that digital natives (Prensky, 2001) who feel completely at ease with the use of digital technology are likely to have better digital skills and may feel comfortable applying them in the work context. This might also be the case for employees in research and development or IT departments, as digital technologies are used to create innovation (Tarafdar et al., 2015). Indeed, empirical findings indicate significant differences in the level of digitalization and digital competence between men and women, different age groups, and types of work activities (Gimpel et al., 2018). Gender was coded as a dummy variable (0 = male; 1 = female). Department affiliation was coded as a dummy variable to control whether employees were affiliated with the innovation and IT department (1) or not (0).
Furthermore, we controlled for autonomy, which is proposed to be a critical factor evoking performance by the job-characteristics model (Hackman & Oldham, 1976). Autonomy was measured by two items (“I can plan and apportion my work load independently”, “I have a say in the work that is assigned to me”; $\alpha^4 = 0.67$).

Lastly, we controlled for task-related and environmental strain and employees’ sickness rate as suggested by the job demands-resources model (Demerouti et al., 2001). Task-related and environmental strain might be perceived as excessive job demands that require sustained physical and/or psychological effort and are, therefore, associated with physiological and/or psychological costs (Demerouti et al., 2001). Consequently, task-related and environmental strain are likely to harm employee health and performance. Task-related strain was measured with two items (“I am not usually under pressure to meet deadlines”, “I can complete my tasks during regular working hours”; $\alpha^5 = 0.76$), while environmental strain was assessed with three items (“the information, materials and equipment (e.g., computers, tools) I need for my work are available to me”, “my workplace is free from unfavorable ambient conditions (e.g., noise, dust)”, “my workplace has sufficient rooms and facilities available”; $\alpha = 0.74, \omega = 0.78$). Employees’ sickness rate was measured by the total number of hours absent due to illness during the period January until April 2018.

2.3.2.1.3 Analytical Procedure

Considering the clustered structure of our data (e.g., one supervisor reporting performance information on multiple employees), we tested our hypotheses by computing a multiple linear regression (MLR) analysis with clustered robust standard errors (CR-SE). MLR analysis is the preferred

---

$^4$ $\omega$ values could not be calculated for constructs with only two items (i.e., task-related strain, autonomy) since two items are not sufficient for the analysis.

$^5$ $\omega$ values could not be calculated for constructs with only two items (i.e., task-related strain, autonomy) since two items are not sufficient for the analysis.
statistical method for examining interaction effects when independent variables and the moderators are measured on a continuous scale (Frazier et al., 2004). The advantage of using CR-SEs instead of a hierarchical linear model (HLM) lies in the fact that CR-SEs allow for performing inferential tests on regression coefficients without the additional step of explicitly modelling the random effects or covariance structures. As a result, random effect assumptions that are required in HLM can be bypassed (McNeish et al., 2017). Furthermore, model $R^2$ and effect size measures appear and are interpreted identically to a single-level model. The statistical adjustment for clustering has an effect only on the standard error estimates of the regression coefficients, leaving the regression coefficient estimates unaffected (McNeish et al., 2017).

The MLR analysis with CR-SEs was conducted following the hierarchical variable entry approach (Hayes, 2013). This technique appeared beneficial since it determines whether allowing the effect of employees’ digital fluency to be contingent on leaders’ or coworkers’ digital fluency yields a better model than one in which the effect of employees’ digital fluency is constrained to be unconditional on the moderators. Hence, we used four regression models where the first model only included control variables, the second model encompassed controls as well as the focal study variables, and the third and fourth models additionally contained the interaction terms, respectively. Finally, we probed the significant interaction to sharpen our understanding of its meaning by plotting the interaction and performing a simple slope analysis using values one standard deviation above and below the mean of the moderator (Cohen & Cohen, 1983).

### 2.3.2.2 Results

#### 2.3.2.2.1 Descriptive Statistics

Table 2.5 summarizes the means, standard deviations, and correlations for all the study variables. Among these variables, we detected several
correlations. Both employees’ digital fluency and coworkers’ digital fluency were significantly and positively related to digital work performance ($r = 0.48, p < 0.01; r = 0.45, p < 0.01$, respectively). Furthermore, employees’ digital fluency significantly correlated with coworkers’ digital fluency ($r = 0.36, p < 0.01$). Surprisingly, leaders’ digital fluency was not related to any focal study variable. Regarding the control variables, gender was significantly related to employees’, leaders’ and coworkers’ digital fluency, indicating that there might be a gender divide. Sufficient distinctiveness between the different measures was assumed as all correlations were considerably lower than 0.80 (Urban & Mayerl, 2014).

2.3.2.2.2 Hypotheses Testing

Hypothesis 1 predicted a main effect of employees’ digital fluency on their digital work performance. As illustrated in Table 2.6 (Model 2), this effect was positive and significant ($\beta = 0.62, p < 0.001$), and thus supported Hypothesis 1. Furthermore, Hypothesis 2 proposed leaders’ digital fluency to moderate the relationship between employees’ digital fluency and their digital work performance. Model 3 in Table 2.6 showed a significant and positive interaction ($\beta = 0.31, p < 0.05$). As the interaction term was significant, we graphically plotted it in Figure 2.2. This graph indicated an increased positive relation of employees’ digital fluency on their work performance under high levels of leaders’ digital fluency than under low levels of leaders’ digital fluency. This graphical effect was further substantiated through simple slope tests. Employees’ digital fluency was significantly related to their digital work performance under high levels of leaders’ digital fluency ($\beta = 0.86, p < 0.001$), but not under low levels of leaders’ digital fluency ($\beta = 0.24, \text{n.s.}$). Lastly, in Hypothesis 3, we proposed that the positive relationship between employees’ digital fluency and their digital work performance is moderated by coworkers’ digital fluency. The results in Table 2.6 (Model 4) did not support this hypothesis as the interaction term was not significant ($\beta = -0.03, \text{n.s.}$).
We also evaluated several alternative models to inspect the robustness of our findings. First, we reran our hypothesized model without control variables to rule out the possibility of impotent control variables bias resulting in similar indicators, as in our main analysis (T. E. Becker, 2005). Second, we used ordinary least squares regressions to replicate the hypothesized relationships. The main effect and the interaction of leaders’ digital fluency and employees’ digital fluency remained significant and positive ($\beta = 0.62, p < 0.001; \beta = 0.31, p < 0.01$). Furthermore, the interaction of coworkers’ digital fluency and employees’ digital fluency was again not significant ($\beta = -0.03$, n.s.). Third, we replaced our dependent variable, digital work performance, by ordinary task performance (“how often has [employee’s name] carried out the core parts of his/her job well within the last six months”; “how often has [employee’s name] ensured his/her tasks were completed properly within the last six months” (Griffin et al., 2007)) and reran our hypothesized model to show the distinctiveness of digital work performance from task performance. The analysis supported that digital work performance was distinctively different from task performance as none of the hypothesized relationships were significant. The results of the robustness checks strengthen our confidence that employees’ digital fluency is indeed a facilitator of employees’ digital work performance and that this effect is moderated by leaders’ level of digital fluency.
### Table 2.5: Descriptive Statistics and Correlations in the Company Sample (Study 2)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>DF E</td>
<td>4.07</td>
<td>0.74</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DF L</td>
<td>4.55</td>
<td>0.50</td>
<td></td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DF C</td>
<td>4.07</td>
<td>0.36</td>
<td>0.36</td>
<td>**</td>
<td>0.01</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Performance</td>
<td>4.23</td>
<td>1.72</td>
<td>0.48</td>
<td>**</td>
<td>0.11</td>
<td>0.45</td>
<td>**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>0.30</td>
<td>0.46</td>
<td>-0.24</td>
<td>**</td>
<td>0.26</td>
<td>**</td>
<td>-0.33</td>
<td>**</td>
<td>-0.18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>41.23</td>
<td>11.55</td>
<td>-0.25</td>
<td>**</td>
<td>0.04</td>
<td>-0.10</td>
<td>-0.17</td>
<td>0.18</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Department</td>
<td>0.16</td>
<td>0.36</td>
<td>0.24</td>
<td>**</td>
<td>0.02</td>
<td>0.50</td>
<td>**</td>
<td>0.00</td>
<td>-0.27</td>
<td>**</td>
<td>-0.16</td>
</tr>
<tr>
<td>Autonomy</td>
<td>3.29</td>
<td>1.00</td>
<td>0.23</td>
<td>**</td>
<td>0.02</td>
<td>0.19</td>
<td>**</td>
<td>0.25</td>
<td>**</td>
<td>0.06</td>
<td>-0.09</td>
</tr>
<tr>
<td>Task</td>
<td>3.06</td>
<td>1.02</td>
<td>-0.07</td>
<td></td>
<td>0.25</td>
<td></td>
<td>0.11</td>
<td>0.00</td>
<td>-0.14</td>
<td>-0.21</td>
<td>**</td>
</tr>
<tr>
<td>Environment</td>
<td>2.69</td>
<td>1.10</td>
<td>0.36</td>
<td></td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.01</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sickness</td>
<td>1.02</td>
<td>0.07</td>
<td>0.22</td>
<td></td>
<td>0.04</td>
<td>0.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Note: N = 195; ** p ( \leq 0.01 ); values are based on two-sided significance testing; SD = standard deviation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

** = environment; sickness = sickness rate.

DF E = employees’ digital fluency; DF L = leaders’ digital fluency; DF C = coworkers’ digital fluency; performance = digital work performance; department = department affiliation; task = task-related strain; environment = environmental strain; sickness = sickness rate.
## 2.3. Methods and Results

### Table 2.6: Regression on Employees’ Digital Work Performance in the Company Sample (Study 2)

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>R-SE</td>
<td>p</td>
<td>β</td>
</tr>
<tr>
<td>Constant</td>
<td>4.28</td>
<td>0.33</td>
<td>***</td>
<td>4.27</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>-0.29</td>
<td>0.39</td>
<td></td>
<td>-0.20</td>
</tr>
<tr>
<td>Age</td>
<td>-0.27</td>
<td>0.17</td>
<td></td>
<td>-0.14</td>
</tr>
<tr>
<td>Department affiliation</td>
<td>-0.17</td>
<td>0.32</td>
<td>*</td>
<td>-0.25</td>
</tr>
<tr>
<td>Autonomy</td>
<td>0.38</td>
<td>0.06</td>
<td>***</td>
<td>0.30</td>
</tr>
<tr>
<td>Task-related strain</td>
<td>0.33</td>
<td>0.12</td>
<td></td>
<td>0.29</td>
</tr>
<tr>
<td>Environmental strain</td>
<td>0.33</td>
<td>0.18</td>
<td>*</td>
<td>0.20</td>
</tr>
<tr>
<td>Sickness rate</td>
<td>-0.44</td>
<td>0.12</td>
<td>*</td>
<td>-0.29</td>
</tr>
<tr>
<td><strong>Main effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employees’ DF</td>
<td>0.62</td>
<td>0.12</td>
<td>***</td>
<td>0.55</td>
</tr>
<tr>
<td>Leaders’ DF</td>
<td>0.38</td>
<td>0.12</td>
<td></td>
<td>0.29</td>
</tr>
<tr>
<td>Coworkers’ DF</td>
<td>-0.29</td>
<td>0.12</td>
<td>*</td>
<td>-0.29</td>
</tr>
<tr>
<td>Interaction terms</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$DF \times DF_L$</td>
<td>0.62</td>
<td>0.12</td>
<td>***</td>
<td>0.55</td>
</tr>
<tr>
<td>$DF \times DF_C$</td>
<td>0.38</td>
<td>0.12</td>
<td></td>
<td>0.29</td>
</tr>
<tr>
<td>$F$</td>
<td>24.81</td>
<td>0.35</td>
<td>0.11</td>
<td>29.38</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.11</td>
<td>0.11</td>
<td></td>
<td>0.04</td>
</tr>
<tr>
<td>$\Delta R^2$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Note.** $N = 195$; $p \leq 0.05$; $** p \leq 0.01$; $*** p \leq 0.001$; $DF =$ digital fluency; $DF_L =$ leaders’ digital fluency; $DF_C =$ coworkers’ digital fluency; $R-SE =$ robust standard errors.
2.4 Discussion

Working with digital technologies is clearly a double-edged sword that has opposite effects on individual work performance (Day et al., 2010). Nonetheless, digital technologies are ubiquitous and are assuming increasing importance in the workplace. Yet, research is only in its infancy to empirically investigate qualities that predispose employees to successfully perform in a digitalized work environment (Oberländer et al., 2020). Therefore, the purpose of this study was to conceptualize and empirically test a competence that enables employees to fulfill their role requirements through digital technologies and, thus, deliver work outcomes. Based on our theorizing and an empirical study of a German manufacturing company, we showed that employees’ digital fluency — consisting of digital
knowledge and digital self-efficacy — positively affects their digital work performance. We further explored the link between employees’ digital fluency and their digital work performance by shedding light on two potential moderators of this relationship. We first examined leaders’ digital fluency level as a relevant boundary condition in the respective relationship. Our findings supported that the effect of employees’ digital fluency on their digital work performance is indeed stronger when leaders have a high level of digital fluency. Contrary to our hypothesis, coworkers’ digital fluency was not found to be a boundary condition in the relationship between employees’ digital fluency and their digital work performance. Yet, we found a direct effect of coworkers’ digital fluency on employees’ digital work performance.

2.4.1 Theoretical Implications

The present investigation contributes to the literature by corroborating and extending prior findings in several ways. We built theory regarding the emergence of digital work performance. We theoretically conceptualized and empirically tested employees’ digital fluency as a new person-specific predictor of digital work performance. Furthermore, we extended this theoretical perspective by taking the role of leaders’ and coworkers’ digital fluency as possible enablers into account. By doing so, we applied well-established theories, such as Campbell et al.’s (1993) influential performance model and the social learning theory (Bandura, 1977), to a new context, integrating it with the growing body of digital workplace literature (Agarwal et al., 2000; Downey & Rainer, 2009; Teo, 2009; Wilfong, 2006). Moreover, the theoretical conceptualization and empirical validation of digital fluency as a higher-order construct based on two distinctive dimensions contributes to clarifying the concept of digital competence. Our study, therefore, corroborates research (Oberländer et al., 2020; Y. Wang & Haggerty, 2009, 2011) that defines digital competence as a multidimensional construct combining a novel ensemble of knowledge, skills,
abilities, and other characteristics. Furthermore, by considering digital fluency in a work setting and demonstrating its relevance for employees’ digital work performance, our research broadens the understanding of the concept of digital competence at work — a context that has largely been neglected by prior research (Oberländer et al., 2020).

A conceivable explanation for the non-significant moderation effect of coworkers’ digital fluency could be that competence alone might not have been enough for coworkers to be perceived as attractive role models. Therefore, coworkers’ digital fluency might not have encouraged employees to engage in a learning process which could have improved employees’ digital work performance. In contrast, leaders were able to capture employees’ attention as attractive role models, since they were not only competent (i.e., digitally fluent), but also of high status (Lefkowitz et al., 1955) and power (Bandura et al., 1963; Lippitt et al., 1952).

The direct effect of coworkers’ digital fluency on employees’ digital work performance can indicate supportive behavior among colleagues. Coworkers might have stepped into the breach for each other if need be. Chiaburu and Harrison (2008) show that coworker support can indeed promote employee task performance. Performance gains can be achieved, for example, by giving critical information (Kogler Hill et al., 1989), and directly helping employees advance toward their work goals (Ensher et al., 2001). Chiaburu and Harrison (2008, p. 1086) highlight that “even when the motives for providing support are centered on the person at the receiving end (e.g., skill development), the net result of coworker support is an improvement in the focal employee’s performance level”. Considering these unexpected findings, a fruitful avenue for future research may be to explore digital fluency on a team level. For example, the role of digital fluency climate within a team and its effect on individual digital work performance appears to be worth exploring.
2.4.2 Limitations and Future Research

We followed the recommendations of Podsakoff et al. (2012) to collect data from two sources, namely, employees and supervisors, and applied a time-lagged design. Despite these methodological strengths, this study also has some limitations that should be considered when interpreting the results.

First, the lack of controlled experiments makes any statements about causal direction provisional. However, models with a reverse causal direction lack an underlying theory and would be logically inconsistent, especially for the effect of employees’ digital fluency on their digital work performance. Furthermore, the causal direction is much less likely to be reversed for the hypothesized relationships, as the predictor variables and outcome were measured with a time lag. Nonetheless, future research might overcome this weakness by applying quasi-experimental or longitudinal research designs to ultimately establish causality.

Second, we used a single-item measure to assess employees’ digital work performance, suggesting concerns related to reliability and accuracy. In the literature, the reliability of single-items measures has been widely discussed (Wanous & Hudy, 2001). Even so, single-item measures are generally accepted for measuring some constructs, such as job satisfaction or turnover intention (Wanous & Hudy, 2001). Still, the results should be treated with caution. Future research may thus benefit from replicating the present study with an extensive digital work performance scale.

Third, we validated the digital fluency scale based on data provided by U.S. and German employees. Although this approach strengthens the validity of the digital fluency scale in the western-oriented cultural context, a fruitful way for future research is to cross-validate the scale with non-Western samples.
2.4.3 Practical Implications

Notwithstanding these limitations, the current study has some practical implications for organizations. Our development and testing of theory regarding the emergence of digital work performance provides a possible point of intervention in the longer term: employees’ digital fluency was found to shape their digital work performance, a positive effect that can even be enhanced by modeling leaders who themselves have a high level of digital fluency. Therefore, a structured training program to promote digital fluency among employees and leaders can be put in place. The training program may include interventions focusing on enhancing both digital knowledge and digital self-efficacy.

An intervention to foster digital knowledge might be to provide employees with extensive training and technical support. Such trainings could be tailored towards particular digital technologies that appear most relevant for organizational business operations. Participation in such trainings may enable employees to gain a deeper understanding of what to do with digital technologies, how to do it and when it makes sense to use them (Arthur et al., 2003). Interventions to promote digital self-efficacy may involve mastery experiences (Bandura, 1986). Research indicates that succeeding in a challenging task provides the strongest information for changing efficacy beliefs (Stajkovic & Luthans, 1998). In a training session, participants can be challenged to complete a task with the help of digital technologies in a taxing context (i.e., high task complexity, limited resources, short time span). Mastering such tasks might evoke and reinforce the feeling “I have what it takes to succeed”.

Leaders can have a powerful impact on the process of increasing employees’ digital fluency, and, thus, need to be adequately prepared. Our results showed that digitally fluent leaders are attractive role models to their followers. In addition, leaders can engage in verbal persuasion (Stajkovic & Luthans, 1998). Leaders can focus on their followers’ appraisal of digital self-efficacy by instilling confidence in them to build employees’ belief
in their competence. Expressing a faith in followers’ digital fluency may be particularly relevant in times when employees face performance challenges and question their personal efficaciousness (Stajkovic & Luthans, 1998).
Local COVID-19 Infections and Daily Employee Exhaustion: A Diary Study of Moderating Factors

Sophia Zimmermann

Abstract

The COVID-19 pandemic has drastically changed many aspects of our society and work life. In this study, I assess how daily variations in employees’ emotional exhaustion are affected by daily variations in infection rates in employees’ communities. Applying the conceptual framework of conservation of resources theory, I argue that surging COVID-19 cases have the potential to be psychologically and physically draining and, thus, positively affect employees’ emotional exhaustion. Furthermore, I assume that employees’ age and extent of working from home are key context factors that influence employees’ strain reaction to the daily COVID-19 surge. Particularly older employees and employees who have little access to working from home are proposed to react with higher emotional exhaustion levels toward rising COVID-19 infections in their proximity. I test the proposed relationships based on an eight-day diary study with largely
a representative data set of the German workforce, which was integrated with official COVID-19 case statistics on the county level. However, my analyses cannot provide support for the hypotheses. Implications for the literature on disrupted and traumatic events, limitations and avenues for future research are discussed.

*Keywords:* COVID-19, emotional exhaustion, diary study, aging, working from home
3.1 Introduction

The COVID-19 pandemic has turned life upside down. The rapid worldwide spread of COVID-19 caught organizations and communities off-guard. The scale of the pandemic is reflected in the exponential increase in new cases every day, requiring organizations and communities to adjust work and life routines continuously. For example, on August 1, 2020, the World Health Organization confirmed 289,321 new COVID-19 cases over the last 24 hours worldwide (World Health Organization, 2020b).

Recent research shows that employees react to the strength or severity of the pandemic primarily with negative psychological states, such as anxiety (Fu et al., 2021; Hillebrandt & Barclay, 2022) and suffering (Wee & Fehr, 2021). Similar stressor-strain relationships can be found in the small body of organizational behavior literature on large-scale disrupted and traumatic events. Extra-organizational stressors defined as “environmental factors outside work that can lead to negative and potentially damaging reaction in individuals” (Byron & Peterson, 2002, p. 896) have been found to spill over into the workplace by influencing employees’ affective states (e.g., stress, burnout) as well as their work behavior (e.g., absenteeism, job satisfaction) (Bacharach & Bamberger, 2007; Bacharach et al., 2008; Byron & Peterson, 2002; Hochwarter et al., 2008; A. M. Ryan et al., 2003; Toker et al., 2015; Vinokur et al., 2011). Consequently, prior research, albeit limited, clearly suggests that the COVID-19 pandemic, and extra-organizational stressors in general, can spill over into the workplace by severely affecting employees. Thus, a central question appears to be which employees are most vulnerable to the distress caused by such extra-organizational stressors and how to protect them.

Research exploring boundary conditions in the COVID-19 context appears to have gained some traction (Hillebrandt & Barclay, 2022; Lin et al., 2021; Wee & Fehr, 2021), but is still considerably small. For this
reason, Yuan et al. (2021) calls for more empirical research on critical contingencies that can protect employees’ work effectiveness from persistent health threats in the workplace as the COVID-19 pandemic unfolds. Furthermore, the limited number of studies that investigate boundary conditions in the COVID-19 context might not be as illuminating, since these studies rely primarily on between-person methodology (D. Liu et al., 2021; Shao et al., 2021; Wee & Fehr, 2021). However, within-person approaches might be more appropriate, since the threat posed by the pandemic tends to be perceived very differently (Al-Jayyousi et al., 2021). Even when taking a broader perspective on the research field, research on large-scale disruptive and traumatic events appears to have mainly focused on understanding employees’ strain reactions (Yuan et al., 2021), neglecting possible boundary conditions in the stressor-strain relationship. Therefore, James (2011, p. 933) emphasizes that an “improved understanding of how organizations can prepare for and respond to disaster […] is clearly needed to enhance their and their employees’ safety and success”.

With this study, I want to address this crucial research gap in the literature by shedding light on potential boundary conditions that either predispose employees to or protect employees from psychological distress caused by the daily number of local COVID-19 cases. I consider the daily fluctuation of COVID-19 cases as acute extra-organizational stressors, since they are unexpected, potentially devastating and originate outside of organizational boundaries (Byron & Peterson, 2002; Hochwarter et al., 2008). With regard to employees’ affective state, I focus on employee emotional exhaustion which refers to “feelings of being overextended and depleted of one’s emotional and physical resources” (Maslach & Leiter, 2008, p. 498). Emotional exhaustion has profound implications for employees’ well-being and work behavior (Carson et al., 2010; Cropanzano et al., 2003; Maslach et al., 2001; Swider & Zimmerman, 2010). Contributing to personal health and business survival, emotional exhaustion is, therefore, a relevant factor to be considered in a disruptive and traumatic context, such as the COVID-19 pandemic. Research suggests that
individuals’ levels of emotional exhaustion fluctuate heavily across days and are influenced by extra-organizational events (Caldas et al., 2021; Kammeyer-Mueller et al., 2016). Extending this line of thought, I expect that emotional exhaustion waxes and wanes in response to the daily local COVID-19 infections.

Drawing on COR theory (Hobfoll, 1988, 1989), I propose that the daily number of local COVID-19 cases may alter employees’ resource allocation, thereby influencing employees’ ability to cope and leading to feelings of being overwhelmed. Since the COVID-19 pandemic puts older employees at greater risk than younger employees (Centers for Disease Control and Prevention, 2020), aging employees are likely to experience enhanced threat of resource loss and actual resource loss. I, therefore, suggest that age moderates the relationship between daily local COVID-19 cases and daily employee exhaustion. However, if employees have the opportunity to work from home as means of social distancing, employees should be able to recover and stockpile resources. The extent of working from home (WFH) may, thus, be a second boundary condition influencing the impact of daily local COVID-19 cases on daily employee exhaustion. I define WFH as “an intense form of home-based telecommuting where the home is the primary work venue” (Hill et al., 2003, p. 222). Combining both contextual factors, older employees with little access to WFH will typically experience the worst effect of local COVID-19 numbers on their emotional exhaustion levels. I test the proposed relationships, as depicted in Figure 3.1, based on an eight-day diary study with largely a representative data set of the German workforce with 389 participants, which was integrated with official COVID-19 case statistics on the county level.

I intend to contribute to the research on disruptive and traumatic events by taking a theory-driven approach to generate critical and timely knowledge for understanding how the COVID-19 surge affects employees. To understand whether employees react with increasing levels of emotional exhaustion to the daily number of local COVID-19 cases is critical
to assess the extent of damage generated by the pandemic. By answering the question of who is particularly vulnerable to stressors at the environmental level and how can organizations prevent extra-organizational stressors from spilling over into the workplace by affecting individual daily emotional exhaustion levels, I further respond to the call by Yuan et al. (2021) for more empirical research on critical contingencies that can protect employees’ work effectiveness from persistent health threats in the workplace as the COVID-19 pandemic unfolds.

Figure 3.1: Conceptual Model Study 2

3.2 Theory Development

3.2.1 Effect of Local COVID-19 Cases on Emotional Exhaus-
tion

COR theory (Hobfoll, 1988, 1989) provides valuable insights for the study of emotional exhaustion. According to this framework, emotional exhaustion is most likely to occur when there is an actual resource loss or a perceived threat of resource loss (Hobfoll, 1988). Hobfoll (1989, p. 516) defines resources “as those objects, personal characteristics, conditions, or energies that are valued by the individual or that serve as a means
3.2. THEORY DEVELOPMENT

for attainment of these objects”. Examples of resources include personal health, children’s or partner’s health and feelings of being safe (Hobfoll, 2001). Building on these basic tenets of COR theory, I argue that employees experiencing an increasing number of daily local COVID-19 cases are prone to exhaustion as rising infection rates are apt to be psychologically and physically draining, hindering or preventing employees’ ability to cope and leading to feelings of being overwhelmed.

An increasing number of daily local COVID-19 cases poses a serious threat to employees’ health. The COVID-19 virus is mainly transmitted via social contact, meaning that surging case numbers in an individual’s local environment increase the risk of infection (World Health Organization, 2020a). Daily local COVID-19 cases, therefore, reflect an individual’s chance to fall ill from the virus and, thus, to endure physical, psychological, and material hardship. Consequently, surging case numbers may put employees in a state of fear of their own health as well as the health of their beloved ones (Fu et al., 2021; J. Hu et al., 2020). Furthermore, employees experiencing surging case numbers have to bear strict government restrictions against the spread of virus, such as limiting social contacts, physical distancing, keeping rooms well ventilated and wearing masks (World Health Organization, 2021). The restrictions can even extend to complete societal and economic shutdowns, as in March and April 2020, when schools, universities, cultural institutions, retail and restaurants closed and any kind of social interaction was limited (Die Bundesregierung, 2020). Therefore, with increasing numbers of daily local COVID-19 cases, the greater the anxiety and pressures are likely to tap employees’ emotional and physical energy reserves and deplete resistance to stress (Caldas et al., 2021; Fu et al., 2021). In this way, employees are proposed to react to the daily number of local COVID-19 cases with increased levels of emotional exhaustion leading to the following hypothesis:

Hypothesis 1: The daily number of local COVID-19 cases affects employees’ daily emotional exhaustion, such that increasing numbers lead to
enhanced levels of emotional exhaustion.

3.2.2 Employee Age and the Effect of Local COVID-19 Cases on Emotional Exhaustion

Current statistics on COVID-19 indicate that the risk of experiencing severe physical symptoms and health impairments rise with chronological age (Centers for Disease Control and Prevention, 2020). Adults over 50 years already have a significantly higher fatality rate than the average 2.3 percent reported worldwide (World Health Organization, 2020c). Not surprisingly, older individuals have been found to perceive a higher risk of dying from COVID-19 (Bruine de Bruin, 2021).

This pronounced illness susceptibility is likely to exacerbate resource loss or perceived threat of resource loss for aging employees as the mortality of elderly employees is thrown into sharp relief (Kanfer et al., 2020). Being reminded of their increased health risk by the daily number of local COVID-19 cases, aging employees are confronted with their anxiety and pressures associated with the pandemic everyday anew. J. Hu et al. (2020, p. 1220) highlight that “when individuals are reminded of mortality in this deadly crisis, they face paralyzing terror, and experience increased nervousness, uncertainty, and apprehension about both their lives and their livelihoods at the moment and in the future”. In this way, the daily COVID-19 surge saps the emotional stamina of aging employees, pulling away even more energy from older as compared to younger employees. I, therefore, argue that aging employees are predisposed to the distress caused by rising infection rates magnifying feelings of being emotionally overextended and drained. Consequently, I propose that the daily local COVID-19 surge and employees’ age interact in their relation to emotional exhaustion leading to the following hypothesis:

Hypothesis 2: Employees’ age moderates the positive relationship between the daily number of local COVID-19 cases and employees’ daily emotional exhaustion, such that the relationship becomes more positive as
COR theory emphasizes that “resource preservation and resource development processes are contingent on supportive versus undermining environmental conditions” (Hobfoll et al., 2018, p. 119). Therefore, organizations can protect their employees from resource loss or perceived threat of resource loss by providing a supportive environment. In the context of the COVID-19 pandemic, a supportive environment might be one that reduces the risk of contracting COVID-19, for example by facilitating social distancing which is considered a key means to reduce virus transmission (Qian & Jiang, 2020). I, therefore, propose the importance of WFH as a supportive environmental factor that expands employees’ capacity and resource pool for mitigating the relationship between the daily local COVID-19 surge and daily emotional exhaustion.

WFH reduces COVID-19 infections by effectively limiting employees’ social contacts (Alipour et al., 2020). For example, home-based teleworkers do not have to commute, meet colleagues and clients face-to-face or have lunch in a crowded company cafeteria. Consequently, employees are not immediately confronted with circumstances which threaten or cause a depletion of resources. I, therefore, argue that, with increasing levels of WFH, employees perceive increasing infection numbers as less threatening and, thus, less psychologically and physical draining. They can take advantage of the favorable situation to conserve emotional and mental energy and develop stockpiles to off-set potential future losses (Lee & Ashforth, 1996; Wright & Cropanzano, 1998). Extensive levels of WFH are likely to give employees a sense of control over their risk of contracting COVID-19 as they can determine to a greater extent how much social contact they expose themselves to. Moreover, a recent study (Baert et al., 2020) provides support for the idea that extended telework is beneficial for em-
ployees during the COVID-19 crisis in terms of health- and work-related outcomes. In a study sample of 1,895 employees, Baert et al. (2020) found that almost half of the participants reported less work-related stress (45.7 percent), deceased chances of burnout in the near future (42.7 percent), better concentration at work (44.8 percent) and more work effectiveness (45.2 percent) due to the extended homework caused by the corona crisis. Consequently, I argue that the extent of WFH is effective in mitigating the positive effect of the daily number of local COVID-19 cases on daily emotional exhaustion leading to the following prediction:

**Hypothesis 3:** Employees’ extent of WFH moderates the positive relationship between the daily number of local COVID-19 cases and employees’ daily emotional exhaustion, such that the relationship becomes less positive as the extent of WFH increases.

### 3.2.4 Interplay between Age, the Extent of Working from Home and the Effect of Local COVID-19 Cases on Emotional Exhaustion

Integrating the prior arguments, I assume that, in the face of rising local COVID-19 cases, older employees react more favorably to extended levels of WFH compared with their younger colleagues. Older employees are likely to experience extreme emotions, such as terror, fear, and distress due to the heightened mortality salience caused by rising infection rates in their environment (Arndt et al., 1997; Janoff-Bulman & Frieze, 1983). In consequence, they have the highest need for social distancing measures that lower their infection risk. If they have access to extended levels of WFH, they might be less likely to perceive the local COVID-19 cases as psychologically and emotionally draining. Moreover, they may be able to recover and stockpile resources to greater extent, since older employees have been found to profit more of extended telework than younger employees (Baert et al., 2020). On the other hand, if they do not have access to the supportive environment of WFH, their emotional exhaustion
is likely to be most adversely affected among all employee groups. The looming threat to their health will deplete their personal resources leading to feelings of being emotionally overextended.

In contrast, younger employees may feel less threatened by rising COVID-19 cases because their lower age indicates lower personal health risks. While they might generally react favorably to WFH, already moderate levels of WFH might suffice to match their needed risk aversion, and a further increase in WFH beyond this need may have a decreasing marginal impact on their emotional exhaustion. In consequence, I formulate the following final hypothesis:

*Hypothesis 4: There is a three-way interaction among the daily number of local COVID-19 cases, employees’ age, and daily extent of WFH on employees’ emotional exhaustion, such that the buffering interaction between COVID-19 cases and WFH is more pronounced as employee age increases.*

### 3.3 Methods

#### 3.3.1 Procedure and Participants

I collected the study data as part of the Konstanz Homeoffice Study (Kunze et al., 2020) during the peak of the first COVID-19 wave in Germany from March 30 through April 9 (based on official government data, April 2, with 6,561 cases, the highest number of newly reported cases in spring 2020). The sample was recruited through a survey company (Respondi), which gave me access to its online panel of participants located across Germany. Survey participants mirrored the German working population in terms of gender structure and age distribution, based on the most recent published data from the German statistical office (Statistisches Bundesamt, 2018). Furthermore, participants were only allowed to participate if they (a) had a working contract, and (b) were currently at least partly working from home. Respondents had to complete a general
survey on day 1 (Monday, March 30) and then participate in eight daily surveys over the next eight workdays. The daily surveys were open from 6 p.m. through 8 a.m. the next morning. Participants received incentives of 0.75€ for the general survey, 0.25€ for each daily survey, and a bonus of 1.00€, if they participated in all eight daily surveys. The initial sample on day 1 consisted of 699 participants, who were mainly male (58 percent), on average 44 years old, and worked 80 percent of their time from home. In line with prior work (e.g., Gabriel et al., 2018; Rosen et al., 2016), I retained data for participants who provided daily data for more than three workdays to assure that the momentary assessments are representative of participant’s individual experiences and are not biased toward days with extreme experiences (Ohly & Gochmann, 2017). This resulted in a final sample of 389 participants who provided 2,874 daily surveys.

3.3.2 Measures

Age as a person-level variable was collected in the general survey on day 1. COVID-19 cases, emotional exhaustion and the extent of WFH were assessed on a daily level for eight consecutive workdays.

3.3.2.1 Age

The chronological age of the participants was captured in the baseline survey in years lived since birth.

3.3.2.2 Daily COVID-19 Cases

To capture daily local COVID-19 cases for every individual participating in my survey, official data released by the Robert Koch Institute (RKI) in Germany were used. The RKI is the government’s central scientific institution for disease control and prevention and provides the number of daily COVID-19 cases disaggregated at the county level. In this way, of-

---

1I did not survey for full two weeks, as the potential ninth day (April 10) was an official holiday in Germany.
ficially confirmed COVID-19 cases in a county could be mapped to each survey participant on a daily level using the postal code provided by the participants. On the last day of my survey, over 119,000 official cases were confirmed in 412 counties in Germany. By law, each laboratory-confirmed COVID-19 case has to be notified to the local public health department and transmitted to the RKI. The RKI visualizes the data and makes them easily accessible on a county-level in an online dashboard and daily situation reports\(^2\). Because of the easy accessibility of the data and the wide coverage of case numbers by the local and national press, most individuals were aware of local COVID-19 outbreaks. I used the absolute numbers of COVID-19 cases in a county around a participant in my analysis, as absolute numbers were the dominant metric of reporting at this time. I lagged this measure by one day \((t - 1)\) to assure that COVID-19 cases temporally proceed the outcome measure, which allows for stronger causal conclusions.

### 3.3.2.3 Daily Emotional Exhaustion

I assessed daily emotional exhaustion using three items from the emotional exhaustion subscale of a German adaptation (Schermuly & Meyer, 2016) of the Maslach Burnout Inventory (Maslach & Jackson, 1981). Following the recommendation for diary studies (Gabriel et al., 2019; Uy et al., 2010), I used a shortened version of the original scale to reduce participant fatigue and adapted the scale for day-specific assessments: “I feel emotionally drained by my work today”, “at the end of today’s working day I feel exhausted” and “I feel burnt out by my work today”. Items were rated on a five-point scale ranging from 1 (\textit{strongly disagree}) to 5 (\textit{strongly agree}). The average coefficient \(\alpha\) across the eight days was 0.93. CFA results showed sufficient standardized regression weights between 0.87 and 0.93\(^3\).

\(^2\)https://experience.arcgis.com/experience/478220adc454480e823b17327b2bf1d4 and https://www.rki.de/DE/Content/InfAZ/N/Neuartiges_Coronavirus/Situationsberichte/Gesamt.html

\(^3\)However, fit indices cannot be calculated since the model is not identified due to its limited number of items (Rigdon, 1995).
3.3.2.4 Daily Extent of Working from Home

Building on prior telecommuting research (Golden & Gajendran, 2019; Golden & Veiga, 2005), the degree of WFH was assessed by asking respondents to indicate the percentage of time they spent teleworking at home that day. Higher scores indicate a greater proportion of time spent working as a home-based teleworker.

3.3.3 Data Analysis

Given the nested data structure (i.e., days nested within persons nested within counties), I tested all hypotheses using three-level mixed-effect models in Stata SE 16. The specification of three-level mixed-effect models appears to be appropriate, since the intraclass correlation coefficient (ICC1) for my criterion measure indicated substantial day-level variation which is a prerequisite for examining day-level relationships using mixed-effect models (Hox, 2010; Raudenbush & Bryk, 2010). An ICC1 of 0.64 for emotional exhaustion indicated that 64 percent of the variance in emotional exhaustion lies between-individuals and 36 percent of variance within-individuals. Furthermore, a three-level model fitted notably better than a two-level model ($\Delta$ AIC = 193.88; $\Delta$ BIC = 187.92; $p = 0.00$).

All day-level variables (i.e., COVID-19 cases, emotional exhaustion, extent of WFH) were treated as Level 1 (within-person) variables, and age as a person-level variable was treated as Level 2 (between-person) variable in the model. Following prior recommendations (Enders & Tofighi, 2007), I centered Level 1 predictors around the respective person-mean and age as a Level 2 predictor around the grand-mean. The person-mean centering of Level 1 variables eliminates between-person variance and provides a pure estimate of day-level relationships as postulated in my hypotheses. Because person-mean centering of the Level 1 predictors removed all stable between-person differences (e.g., demographics, personality, response tendencies), such stable between-person differences could not bias my es-
3.4 Results

3.4.1 Descriptive Statistics

Descriptive statistics and day- and person-level correlations are displayed in Table 3.1. On the within-person level, the daily number of local COVID-19 cases significantly correlated with emotional exhaustion ($r = -0.05$, $p = 0.01$) and the extent of WFH ($r = -0.06$, $p = 0.00$). On the between-person level, emotional exhaustion was significantly correlated with age ($r = -0.22$, $p = 0.00$) and extent of WFH ($r = -0.12$, $p = 0.02$).

Table 3.1: Means, Standard Deviations, and Correlations of Study Variables

<table>
<thead>
<tr>
<th>#</th>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Exhaustion</td>
<td>2.15</td>
<td>0.96</td>
<td></td>
<td>-0.05**</td>
<td></td>
<td>-0.00</td>
</tr>
<tr>
<td>2</td>
<td>COVID-19 cases</td>
<td>0.51</td>
<td>0.75</td>
<td>-0.06</td>
<td></td>
<td></td>
<td>-0.06**</td>
</tr>
<tr>
<td>3</td>
<td>Age</td>
<td>44.90</td>
<td>11.91</td>
<td>-0.22***</td>
<td>0.04</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Extent of WFH</td>
<td>86.98</td>
<td>18.30</td>
<td>-0.12*</td>
<td>0.03</td>
<td>0.03</td>
<td></td>
</tr>
</tbody>
</table>

Note. Correlations above the diagonal are day-level correlations ($N = 2,874$). Correlations below the diagonal are person-level correlations ($N = 389$). Day-level variables were aggregated to the between-person level prior to computing person-level correlations. Because nesting of observations in persons is not accounted for significance, values for day-level correlations should be interpreted with caution. Means and standard deviations (SD) were computed at the person-level of analysis. COVID-19 cases are rescaled (COVID-19 cases / 1000). Exhaustion = emotional exhaustion; WFH = working from home. * $p \leq 0.05$ (two-tailed); ** $p \leq 0.01$ (two-tailed); *** $p \leq 0.001$ (two-tailed).
3.4.2 Hypotheses Testing

Hypothesis 1 suggested that the daily number of local COVID-19 cases has a positive effect on daily emotional exhaustion. I specified a model containing the direct effects of my focal variables on emotional exhaustion. As presented in Model 1 in Table 3.2, I found the effect of daily COVID-19 cases on daily emotional exhaustion to be not significant ($B = 0.03$, $p = 0.85$). Thus, Hypothesis 1 is not supported. Yet, it is noteworthy that Model 1, including a random effect for COVID-19 cases, fitted notably better than a model with a fixed slope for daily COVID-19 cases ($\Delta -2 \log \text{likelihood} = 14.30$, $p = 0.00$; $\Delta \text{AIC} = 24.59$). The improvement in model fit indicates that the effect of COVID-19 cases on emotional exhaustion notably varies between observations, thereby pointing to the relevance of moderators of the relationship.

In the next step, I examined if the effect of daily COVID-19 cases in a county on daily emotional exhaustion is more positive for older employees, as suggested in Hypothesis 2. The coefficient of the cross-level interaction between daily COVID-19 cases and chronological age in Model 2 in Table 3.2 is not significant ($B = -0.01$, $p = 0.46$), rejecting Hypothesis 2. Next, I tested Hypothesis 3, which suggests that COVID-19 cases are less positively related to employee daily emotional exhaustion as the extent of WFH increases. The two-way interaction between COVID-19 cases and the extent of WFH in Model 3 in Table 3.2 is not significant ($B = 0.01$, $p = 0.45$). Thus, Hypothesis 3 is not supported. In the last step, I tested if older employees’ emotional exhaustion is most responsive to increasing levels of WFH in times of rising COVID-19 cases. As shown in Model 4 in Table 3.2, the three-way interaction among daily COVID-19 cases, age, and the daily extent of WFH is not significant ($B = -0.00$, $p = 0.93$). Thus, Hypothesis 4 is not supported.
3.4.3 Sensitivity Test

While the time-lagged data from different sources employed in my study facilitate causal inference, Antonakis et al. (2019) recently highlighted that a threat to the validity of the mixed-effect model is when the unobserved variation, due to the hierarchical data structure, is not correctly modeled. This would lead to biased estimates that preclude a causal interpretation. In my study context, nesting is complex, with individuals nested in jobs, teams, companies, and districts. As I did not model all the levels in my data for the sake of parsimony, I checked if my results were biased by the omission of some levels and followed Antonakis et al.’s (2019) recommendation and included person-means of the Level 1 predictors (i.e., COVID-19 cases and the extent of WFH) as controls. After controlling for person-means, my results remained unchanged, making me confident that I accurately specified my mixed-effect models.

3.5 Discussion

My research used the COVID-19 pandemic, a traumatic and disruptive event, as an empirical referent to explore the emotional reaction of employees to extra-organizational stressors, such as the daily number of local COVID-19 cases. Grounded in COR theory (Hobfoll, 1988, 1989), I proposed employees experiencing increasing numbers of daily local COVID-19 cases to be prone to emotional exhaustion as rising infection rates are apt to be psychologically and physically draining. Furthermore, I argued that employees’ age and extent of WFH influence employees’ strain reaction to the daily COVID-19 surge. Depending on their age and extent of WFH, employees may vary in their perception of the extent to which rising infection rates pose a threat to them. However, the analyses could not provide support for the proposed hypotheses. Contrary to my expectation, my research revealed a significant negative effect of age on daily emotional exhaustion. Nonetheless, the current study provides meaningful implica-
Table 3.2: Multilevel Model Predicting Daily Emotional Exhaustion

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.23</td>
<td>2.23</td>
<td>2.23</td>
<td>2.23</td>
</tr>
<tr>
<td>B</td>
<td>0.06</td>
<td>0.06</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>SE</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>p</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**Main effects**
- **COVID**
  - Model 1: 0.04, SE: 0.16, p: 0.79
  - Model 2: 0.02, SE: 0.15, p: 0.90
  - Model 3: 0.03, SE: 0.15, p: 0.85
  - Model 4: 0.03, SE: 0.15, p: 0.85

- **Age**
  - Model 1: -0.02, SE: 0.00, p: 0.00
  - Model 2: -0.02, SE: 0.00, p: 0.00
  - Model 3: -0.02, SE: 0.00, p: 0.00
  - Model 4: -0.02, SE: 0.00, p: 0.00

- **WFH**
  - Model 1: -0.00, SE: 0.00, p: 0.59
  - Model 2: -0.00, SE: 0.00, p: 0.57
  - Model 3: -0.00, SE: 0.00, p: 0.59
  - Model 4: -0.00, SE: 0.00, p: 0.59

**Interaction terms**
- **COVID** × **Age**
  - Model 1: -0.01, SE: 0.01, p: 0.46
- **COVID** × **WFH**
  - Model 1: 0.01, SE: 0.01, p: 0.45
- **COVID** × **Age** × **WFH**
  - Model 1: -0.00, SE: 0.00, p: 0.93

**Time Dummies**
- Model 1: YES
- Model 2: YES
- Model 3: YES
- Model 4: YES

**Number of parameters**: 16, 17, 17, 17

**-2 log likelihood**: 3488.44, 3488.02, 3488.44, 3488.17

**AIC**: 7008.89, 7010.04, 7010.34, 7010.88

**Note.** N = 2,874 at the day-level and N = 389 at the person-level. Level 1 predictors (COVID, WFH) were centered at each person’s mean. Level 2 predictor (age) is centered around the grand-mean. COVID variable is rescaled (COVID-19 cases / 1000). Time is dummy coded and modeled as fixed effect. Unstandardized effects are reported. Robust standard errors account for potential heteroscedasticity effects. COVID = COVID-19 cases; WFH = working from home.
3.5. DISCUSSION

3.5.1 Theoretical Implications

I contribute to the research on disruptive and traumatic events by generating critical and timely knowledge about potential boundary conditions (i.e., age and extent of WFH) that either predispose employees to or protect employees from the psychological distress caused by extra-organizational stressors. By doing so, I respond to the call by Yuan et al. (2021) for more empirical research on critical contingencies that can protect employees’ work effectiveness from persistent health threats in the workplace as the COVID-19 pandemic unfolds.

Furthermore, my analyses revealed that aging employees experience significantly lower levels of daily emotional exhaustion. This finding corroborates recent research by Kimhi et al. (2020) showing that older age predicts lower levels of sense of danger and distress symptoms. Moreover, it reaffirms the strand of literature highlighting older workers’ ability to maintain well-being on days with high-intensity negative events (Scheibe, 2021; Scheibe & Moghimi, 2021). A possible reason why older workers, despite their pronounced illness susceptibility, appear to be better able to maintain emotional functioning during the COVID-19 pandemic could be that older workers use more adaptive emotion-regulation strategies (e.g., reappraisal, problem-solving, or deep acting) and less maladaptive strategies (e.g., suppression, surface acting) than younger employees (Dahling & Perez, 2010; Hertel et al., 2015; Scheibe et al., 2016).

3.5.2 Limitations and Future Research

Despite multiple strengths, such as repeated measurement design over eight workdays and daily COVID-19 cases as an exogenous independent variable, my research has several limitations. First, the daily infection numbers might not have varied enough over the observed eight-day pe-
period to evoke significant changes in employees’ emotional reaction. The ICC1 of 0.97 for the daily number of local COVID-19 cases indicates that 97 percent of the variance in the daily infection numbers lied between-individuals and only three percent of variance within-individuals. Future research is, therefore, encouraged to replicate my findings by using a sufficiently long study period for clarification.

Second, my sample, also being representative in terms of age and gender for the German working population, was restricted to mainly white-collar workers with the potential to work remotely. However, blue-collar workers compared to white-collar workers might have been more likely to experience emotional exhaustion, since they are often even more at risk of catching the virus based on their physical presence at their workplace. This is, therefore, an opportunity for future work to extend this sample to blue-collar workers to investigate whether the proposed effects can be observed.

Third, I used a shortened version of the original emotional exhaustion scale to reduce participant fatigue. However, using a short measure could have induced measurement errors because the content coverage of a short scale is deficient compared to the original measure as fewer items are less likely to cover the full construct domain (Gabriel et al., 2019).

Forth, my conceptualization of the daily number of local COVID-19 cases requires that individuals are, to some extent, aware of the broad shapes of the pandemic. However, I consider this assumption reasonable. The coverage of case numbers by the local and national press was broad early on in the pandemic. Moreover, people follow crises closely and the knowledge of the pandemic was widespread early (Fu et al., 2021).

Lastly, although the COVID-19 infection numbers dramatically increased during the study period, employees might have based their assessment of the risk posed by the pandemic on other metrics, such as the intensive care bed occupancy rate or the assessment of the operational situation in intensive care units. Official data released by the DIVI-
Intensivregister\(^4\) in Germany indicates that more than 40 percent of the intensive care beds were available during the study period. Furthermore, only three to seven percent of the hospitals assessed the overall operation of their intensive care unit as restricted in terms of staff, rooms and material during the study period. Therefore, employees might have been less affected by the COVID-19 numbers and considered social distancing measures, such as WFH, less relevant to reduce one’s risk to endure physical, psychological, and material hardship. Future work may, thus, use several metrics to capture the health risk posed by the COVID-19 pandemic.

### 3.5.3 Practical Implications

Contrary to the expectation that the pandemic takes a toll on the emotional functioning of employees, the present study does not find support for severe emotional exhaustion among employees in response to the pandemic at the workplace. My result echoes the findings by Zacher and Rudolph (2020) who found a decline in negative affect between March and May 2020. Since both studies used highly activated affect items to measure the affective response to COVID-19 (e.g., burnt out, exhausted), it seems reasonable to discuss whether the pandemic triggers less strong affective responses in employees than previously thought. If this were the case, the implications for organizations would have to be re-assessed. I, therefore, emphasize the call by Zacher and Rudolph (2020) to examine whether employees’ low-activated affect increased during the pandemic.

### 3.6 Conclusion

The COVID-19 pandemic is an unprecedented situation for employees, firms, and society as a whole. My study is among the first to explore the emotional reaction of employees to daily extra-organizational stressors in

\(^4\)The DIVI Intensivregister visualizes the data and makes them easily accessible in an online dashboard and daily situation reports. Data available at: https://www.intensivregister.de/#/aktuelle-lage/zeitreihen
form of local infection numbers. In particular, I built on COR theory to identify potential boundary conditions (i.e., age and extent of WFH) that either predispose employees to or protect employees from psychological distress caused by the daily COVID-19 surge. Beyond the current pandemic, the study contributes to the literature that links large-scale disrupted and traumatic events with organizational behavior.
New Normal, but Good Normal? Testing the Effect of a Hybrid Way of Working on Employee Work Effectiveness

Sophia Zimmermann

Abstract

The COVID-19 pandemic has made telecommuting the “new normal”. The increased flexibility in the location of work raises the question of whether employees’ work effectiveness varies when they telecommute to varying extents throughout the week. Applying the conceptual framework of conservation of resources theory, the current study addresses this critical issue by developing and testing a conceptual model that highlights how employees’ work effectiveness, as reflected in work performance and emotional exhaustion, waxes and wanes in response to employees’ extent of telecommuting during a workweek. Furthermore, the study explores the moderating role of self-goal setting in this process. Results from a panel study of German employees conducted over 1.5 years provide full support for a u-shaped within-person effect of the weekly extent of telecommuting on employees’ weekly work performance. Employees appeared to perform
best when they telecommuted a little or a lot throughout the week, but they appeared to lose seven percent of their work performance at an intermediate level of telecommuting (i.e., 52 percent). Furthermore, the results provide indications for an inversely u-shaped effect of the weekly extent of telecommuting on emotional exhaustion. Theoretical and practical implications are discussed.

Keywords: telecommuting, employee work effectiveness, self-goal setting
4.1 Introduction

Telecommuting has become the “new normal” as the COVID-19 pandemic has been a catalyst for telecommuting to evolve from a niche phenomenon to one that affects a large proportion of the workforce. For example, only 12.3 percent of U.S. workers telecommuted fulltime before the pandemic, while 47.7 percent were fully remote in April 2020 and still 22.9 percent project being remote in 2025 (Ozimek, 2020). Consequently, an increasing number of organizations appear to grant their employees more power to decide where they perform their work. Employees can either choose to telecommute only a little and work predominately at the office, or they can opt for the opposite and telecommute throughout the week. Yet another option is that employees telecommute at an intermediate level and move rather freely between work locations, from the office to another location, and back again to do their work during the week, which is also known as a hybrid way of working (Halford, 2005). Indeed, many employees appear to welcome the option to telecommute at an intermediate level. Research by Bloom (2020) indicates that 55 percent of 2,500 studied American workers prefer some mix of office and home time. Furthermore, Barrero et al. (2021, p. 2) point out that “desires to work from home part of the week are pervasive across groups defined by age, education, gender, earnings, and family circumstances”.

Yet the increased flexibility in the location of work has also sparked a discussion among employers about the right handling of telecommuting in a future post-pandemic workplace. While only a few employers appear to embrace telecommuting, many others seem to be reluctant towards telecommuting or even reject it completely, like Netflix CEO Reed Hastings who expressed strong opposition to telecommuting: “I don’t see any positives. Not being able to get together in person, particularly internationally, is a pure negative” (Flint, 2020; Thomas & Cutter, 2021).

At the heart of the discussion appears to be the concern that mak-
ing the location of work permanently flexible will jeopardize employees’ work effectiveness over time. However, empirical evidence seems to paint a more positive picture. Within-person studies acknowledging a dynamic in the relationship between telecommuting and employee work effectiveness indicate that employees generally have a more positive work experience on telecommuting days compared to office days. In particular, when telecommuting compared to working in the office employees appear to have higher levels of job performance (Delanoeije & Verbruggen, 2020; Vega et al., 2015), work engagement (Delanoeije & Verbruggen, 2020), job satisfaction (Vega et al., 2015), and job-related positive affective well-being (Anderson et al., 2015). Furthermore, employees’ ability to concentrate appears to be higher and their need for recovery appears to be lower on home days than on office days (Biron & van Veldhoven, 2016).

However, prior research appears to have mainly focused on the day-to-day phenomenological experience of working at home (or at another location away from the office) versus working at the office. Accordingly, telecommuting was nearly always measured by asking participants to place themselves in one set of categories each day (i.e., working at the office or working at home). Yet this dichotomous measurement approach may not be able to explain nuances in the variance of telecommuting and therefore may not provide a realistic assessment of how telecommuting is applied. For this reason, Golden and Gajendran (2019) advocate measuring telecommuting by asking employees to indicate the extent to which they spent telecommuting in a given week. Furthermore, the time span over which data were collected in previous studies seems to range from five days (Vega et al., 2015), to two weeks (Anderson et al., 2015; Delanoeije & Verbruggen, 2020), and three weeks (Biron & van Veldhoven, 2016). However, it is conceivable that the short-term effect of telecommuting on employee work effectiveness differs from the long-term effect. For example, a hybrid way of working could promote employee work effectiveness

---

1One exception is Andel et al. (2021) who conducted a weekly diary study on loneliness and self-compassion in a telecommuting context.
in a specific period of time, but switching between work locations might prove ineffective in the long run. Consequently, the goal of the study is to explore the impact of the weekly extent of telecommuting on employees’ weekly work effectiveness at the within-person level over a long period of time (i.e., 1.5 years).

In particular, I focus on behavioral and affective indicators of employee work effectiveness: work performance which refers to the fulfillment of employees’ task requirements (Sonnentag et al., 2008) and emotional exhaustion which is defined as “feelings of being overextended and depleted of one’s emotional and physical resources” (Maslach & Leiter, 2008, p. 498). Individual work performance and emotional exhaustion are of high relevance for organizations and employees alike.

Considering work performance, exerting high performance when accomplishing tasks has been shown to result in satisfaction, feelings of self-efficacy and mastery (Bandura, 1997; Kanfer & Ackerman, 2005). Moreover, high performing employees are likely to have better career opportunities than those employees who perform at moderate or low levels (van Scotter et al., 2000). Emotional exhaustion is “the central quality of burnout” (Maslach et al., 2001, p. 402) and has profound implications for employees’ well-being and work-related behavior. For example, emotional exhaustion has been found to promote absenteeism, turnover (Swider & Zimmerman, 2010), and attrition (Carson et al., 2010) and to mitigate organizational citizenship behavior towards the organization and the leader (Cropanzano et al., 2003). Therefore, work performance and emotional exhaustion are crucial dimensions of employee work effectiveness to be considered in the current upheaval in the world of work.

Drawing on COR theory (Hobfoll, 1988, 1989), I argue that the within-person effect of the weekly extent of telecommuting on employees’ weekly work effectiveness is curvilinear. More specifically, I propose the effect to be u-shaped for the relationship between the extent of telecommuting and work performance and inversely u-shaped for the relationship between the
extent of telecommuting and emotional exhaustion.

I suggest that an office environment where employees telecommute only a little (i.e., about 0 percent) and a remote environment where employees telecommute a lot (i.e., about 100 percent) provide employees with supportive conditions enabling them to acquire resources. I further argue that these surplus resources, on the one hand, protect employees from emotional exhaustion and, on the other hand, are reinvested into employees’ work performance. At intermediate levels of telecommuting, however, employees are proposed to lose resources, since moving regularly between work locations is likely to sap employees’ physical and emotional stamina, resulting in lower levels of weekly work performance and higher levels of weekly emotional exhaustion. Since prior research has highlighted the relevance of self-regulatory strategies in the context of telecommuting (Lapierre & Allen, 2012; Müller & Niessen, 2019; Raghuram & Wiesenfeld, 2004), I further investigate whether employees’ self-goal setting acts as a boundary condition (cross-level moderator) in the relationship between the weekly extent of telecommuting and employees’ weekly work effectiveness.

To test the theoretical model, as depicted in Figure 4.1, I adopt a longitudinal data collection and analysis approach. I collected panel data as part of the Konstanz Homeoffice Study (Kunze et al., 2020) from German employees by a general online survey in March 2020 and five consecutive online surveys from May 2020 to November 2021. Hypotheses are tested with mixed effects models using Stata 16. In doing so, I intend to contribute to theory and practice by building on the core tenets of COR theory (Hobfoll, 1988, 1989) to generate critical and timely knowledge for understanding the within-person effect of the weekly extent of telecommuting on employees’ weekly work effectiveness. First, I aim to extend the literature on telecommuting at the within-person level (Anderson et al., 2015; Biron & van Veldhoven, 2016; Delanoeije & Verbruggen, 2020; Vega et al., 2015) by adopting a more nuanced measurement approach.
than a dichotomous assessment and extending the time period of data collection. Second, exploring the possibility of a curvilinear relationship between the weekly extent of telecommuting and weekly work effectiveness may add to the literature proposing the impact of telecommuting on employee outcomes to be non-linear (Golden, 2006b; Golden & Veiga, 2005). Third, by investigating self-goal setting as a potential moderator in the relationship between the weekly extent of telecommuting and weekly work effectiveness, I intend to corroborate literature emphasizing the relevance of self-regulatory strategies in the context of telecommuting (Lapierre & Allen, 2012; Müller & Niessen, 2019; Raghuram & Wiesenfeld, 2004). Lastly, understanding whether employees’ work effectiveness varies depending on employees’ weekly extent of telecommuting can be highly relevant for HR managers, leaders and employees alike as they all face the challenge of adapting to a post-pandemic future of work in which a hybrid way of working is possibly here to stay (Choudhury, 2020; Lufkin, 2022).

**Figure 4.1:** Conceptual Model Study 3
4.2 Theory Development

4.2.1 The Curvilinear Relationship between the Weekly Extent of Telecommuting and Weekly Work Effectiveness

According to COR theory (Hobfoll, 1988, 1989), “resource preservation and resource development processes are contingent on supportive versus undermining environmental conditions” (Hobfoll et al., 2018, p. 119). Building on this basic tenet, I argue that both an office environment where employees telecommute only a little (i.e., about 0 percent) and a remote environment where employees telecommute a lot (i.e., about 100 percent) provide employees with supportive conditions enabling them to stockpile resources. These surplus resources are, in turn, proposed to strengthen employees’ ability to cope and prevent feelings of being overwhelmed. Furthermore, employees are argued to channel the surplus resources towards their work, since individuals are likely to invest resources in ways that maximize their returns, which means recirculating resources in domains that are most consistent or aligned with their content (Hobfoll, 2001). Thus, I suggest that employees show lower levels of weekly emotional exhaustion and higher levels of weekly work performance when they telecommute to a low (i.e., about 0 percent) and a high (i.e., about 100 percent) extent throughout the week. In contrast, a hybrid way of working (i.e., about 50 percent of telecommuting) is proposed to undermine employees’ resource preservation by increasing the risk of resource loss, since switching regularly between work locations throughout the week is likely to cost energetic, cognitive, and emotional resources. I, therefore, argue that employees show higher levels of weekly emotional exhaustion and lower levels of weekly work performance when they telecommute at an intermediate level (i.e., about 50 percent).

Taken together, I assume employees’ weekly work effectiveness to be highest when employees telecommute a little or a lot during the week, and lowest when employees telecommute a medium amount during the week.
Consequently, I hypothesize the within-person effect of the weekly extent of telecommuting on employees’ weekly work effectiveness to be curvilinear. In particular, I propose the effect to be u-shaped for the relationship between the extent of telecommuting and work performance and inversely u-shaped for the relationship between the extent of telecommuting and emotional exhaustion.

At low levels of weekly telecommuting (i.e., about 0 percent) employees are likely to gain resources from being physically close to their colleagues and leader as well as from the office routine. Employees who telecommute only a little during the week may be able to stockpile resources, since their physical proximity supports them in building and maintaining instrumental and social relationships at work (Khazanchi et al., 2018). Employees who work predominately at the office are likely to have frequent face-to-face interactions with their colleagues as their physical closeness allows them to naturally interact with their colleagues through chance encounters and “stopping by” the desk (Boutellier et al., 2008; Zahn, 1991). In this way, they may have plenty of opportunities to easily share professional information as well as build and nurture a personal relationship with their co-workers and their leader. Indeed, prior research has shown that physical proximity encourages knowledge transfer (Agrawal et al., 2008) and collaborative behavior among colleagues (Kabo et al., 2015; Wineman et al., 2009). Moreover, close yet unplanned encounters with coworkers have been found to encourage affinity, trust, and camaraderie among colleagues (Sarbaugh-Thompson & Feldman, 1998) as employees can discover common interests and share personal aspects of their lives in social conversions. In this vein, existing research has demonstrated the importance of social exchange relationships at work as predictors of employee performance and emotional exhaustion (Banks et al., 2014; Dulebohn et al., 2012; Schermuly & Meyer, 2016). In addition, working predominately at the office throughout the week is likely to provide “some sort of temporal and spatial framework that structures and organizes employees’ daily routines (e.g., fixed working hours and lunch break, spatial separation from
private life demands)” (Müller & Niessen, 2019, p. 883). Following a given office routine may create an ease in the daily life of employees allowing them to devote less cognitive and emotional energy to managing themselves. In this way, telecommuting at a low level throughout the week is argued to free up surplus resources beneficial for employees’ weekly work effectiveness.

Opportunities to accumulate resources may also open up at high levels of weekly telecommuting (i.e., about 100 percent). Employees can conserve emotional and mental energy as working remotely throughout the week mitigates stressful demands associated with commuting, referring to the hassles involved in movement to and from the central office (e.g., heavy traffic and mental work load while driving) (Guimares & Dallow, 1999; Hartig et al., 2007; Recarte & Nunes, 2003). Correspondingly, prior research (Gerpott et al., 2022) has shown that day-specific aversive commutes negatively affect motivational and behavioral indicators of employee work effectiveness through the depletion of employees’ regulatory resources and flow experiences. Moreover, high levels of weekly telecommuting may provide employees with enhanced autonomy (Gajendran et al., 2015), which has been highlighted as a critical resource for employees’ optimal functioning as well as their psychological and physical well-being in the workplace (Bakker & Demerouti, 2007; R. M. Ryan & Deci, 2000). High levels of autonomy are likely to energize, direct, and sustain employees’ work effectiveness as greater autonomy expands employees’ capacity to cope with work demands (Bakker & Demerouti, 2007) and allows employees to alter their work routines in ways to better fit their productivity rhythms and work style (D. G. Allen et al., 2003; Vega et al., 2015). Indeed, prior research has shown that autonomy decreases emotional exhaustion (Fernet et al., 2013; Maslach et al., 2001) and further acts as an intervening variable between telecommuting and supervisor-rated task and contextual performance (Gajendran et al., 2015). Likewise, employees can gain resources from a better fit between aspects of work and the location of work when working remotely throughout the week (Golden &
4.2. THEORY DEVELOPMENT

Gajendran, 2019). A telecommuting environment allows for fewer interruptions, such as background noise and overhearing other people talking nearby (Fonner & Roloff, 2010). Thus, employees can better concentrate at work and, therefore, avoid depleting their resources and conserve their emotional and mental energy (Biron & van Veldhoven, 2016). Correspondingly, empirical research has shown that impaired concentration on one’s tasks is likely to weaken one’s ability to satisfy the need for competence and, thus, result in lower motivation (Arvey et al., 1990; Deci & Ryan, 2000) and poorer performance (Demerouti et al., 2007; van der Linden et al., 2005). Therefore, working predominately in a telecommuting environment throughout the week may support employees in reaching a peak state of work effectiveness.

In contrast, at intermediate levels of weekly telecommuting (i.e., about 50 percent), switching regularly between work locations throughout the week may come at substantial transition costs in terms of resource losses. Adopting a hybrid way of working, employees need to constantly adapt to fundamentally different work routines. On the one hand, working predominately at the office is likely to offer clear temporal and physical boundaries, while on the other hand, working remotely throughout the week may provide extensive flexibility in terms of time and space (Müller & Niessen, 2019). Continuously adapting to these very different routines is apt to be psychologically and physically draining. Furthermore, switching regularly between work locations during the week may require intensive planning and communication. A myriad of things need to be considered and organized, otherwise telecommuting at an intermediate level is likely to cause a great deal of chaos. For example, can upcoming meetings be held in person or online? What kind of tasks can be performed at the office or remotely, given potential material and access restrictions? When will childcare and transportation be needed? In addition, employees may need to discuss and coordinate these plans with colleagues, the supervisor and family members. Consequently, the decision to telecommute at an intermediate level throughout the week is likely to be taken in expense
of employees’ weekly work effectiveness (Hockey, 1997). The effort associated with changing regularly between work locations (i.e., continuously adapting, planning, organizing, communicating etc.) may consume resources and tap employees’ emotional and physical energy reserves. This resource loss might in turn result in greater emotional exhaustion and poorer weekly work performance. In support, prior empirical evidence indicates that the threat and actual loss of resources has a negative effect on in-role performance (Halbesleben & Bowler, 2007; Halbesleben et al., 2013) and adaptive task performance (Niessen & Jimmieson, 2016). Furthermore, research has shown that hindrance demands (e.g., administrative hassles and role-conflict) were positively related to employee burnout (Crawford et al., 2010).

The aforementioned set of arguments leads me to propose that telecommuting only a little or a lot throughout the week frees up resources for core work effectiveness among employees which is reflected by higher levels of weekly work performance and lower levels of weekly emotional exhaustion. Telecommuting at an intermediate level, however, is argued to lead to resource loss resulting in lower levels of weekly work performance and higher levels of weekly emotional exhaustion. Formally stated:

**Hypothesis 1a:** The within-person effect of the weekly extent of telecommuting on weekly work performance is curvilinear in the shape of a “U”.

**Hypothesis 1b:** The within-person effect of the weekly extent of telecommuting on weekly emotional exhaustion is curvilinear in the shape of an inverted “U”.

### 4.2.2 The Moderating Role of General Self-goal Setting

An emerging line of literature (Halbesleben & Bowler, 2007; Halbesleben et al., 2013; Hobfoll et al., 2018) highlights the role of self-regulation in the resource investment process. Building on Carver and Scheier (1982), self-regulation is understood as “a systematic process of human behavior that provides individuals with the capacity to adjust their actions and
goals to achieve desired results” (Jackson et al., 2000, p. 275). Consistent with the COR principle, self-regulation is proposed to enable employees to decide how to best invest resources in order to maximize their returns as well as to readjust their investment process when experiencing resource losses (Hobfoll, 2001; Hobfoll et al., 2018). Employees pursuing a strategy of self-regulation might, therefore, be better able to manage their resources, suggesting that a self-regulation strategy may act as a boundary condition in the curvilinear relationship between the weekly extent of telecommuting and weekly work effectiveness.

A self-regulation strategy that has been found to be relevant in the context of telecommuting is self-goal setting (Müller & Niessen, 2019) which is defined as the process in which individuals set themselves personal goals (Houghton & Neck, 2002). Through conscious and intentional self-goal-setting processes, employees appear to increase their self-regulatory effectiveness in several ways. When employees set themselves difficult and specific goals, they increase their effort and are better able to channel their resources (e.g., attention, time) towards goal attainment which is likely to be reflected in enhanced work performance and reduced emotional exhaustion (Locke & Latham, 2002; Neck & Houghton, 2006). A large body of research has repeatedly demonstrated that the act of setting and accepting challenging and specific goals can have a dramatic effect in motivating individual work performance (Locke & Latham, 1990, 2002; Robison et al., 2021). Moreover, research indicates that employees experience less emotional exhaustion when they set themselves high performance goals (Welsh et al., 2020).

Building on these arguments, I propose that self-goal setting influences the degree to which an intermediate level of weekly telecommuting actually translates into resource loss. Self-goal setting might empower employees to better deal with a hybrid way of working. Through higher levels of effort and a goal-directed management of resources (Houghton & Neck, 2002; Locke & Latham, 2002), employees might lose fewer resources to
the process of switching between work locations. Therefore, an employee with high levels of self-goal setting should experience enhanced weekly work performance and less emotional exhaustion when telecommuting at an intermediate level throughout the week than an employee with low levels of self-goal setting. Thus, I expect the curvilinear relationship between the weekly extent of telecommuting and weekly work effectiveness, as reflected in weekly work performance and weekly emotional exhaustion, to be non-significant for employees with high levels of self-goal setting.

In the absence of an intentional goal-setting process, employees might be less motivated to adjust their resource investment process and, thus, should be less able to prevent resource losses at an intermediate level of telecommuting. I therefore expect the curvilinear relationship between the weekly extent of telecommuting and weekly work effectiveness, as reflected in weekly work performance and weekly emotional exhaustion, to be stronger for employees with low levels of self-goal setting.

In sum, employees’ level of self-goal setting is proposed to moderate the curvilinear relationship between the weekly extent of telecommuting and weekly work effectiveness, as reflected in weekly work performance and weekly emotional exhaustion, leading to the following hypotheses:

**Hypothesis 2a**: Employees’ level of self-goal setting moderates the u-shaped relationship between the weekly extent of telecommuting and weekly work performance in such a way that employees with a high level of self-goal setting exert higher levels of weekly work performance in response to intermediate levels of weekly telecommuting than employees with lower levels of self-goal setting.

**Hypothesis 2b**: Employees’ level of self-goal setting moderates the inverted u-shaped relationship between the weekly extent of telecommuting and weekly emotional exhaustion in such a way that employees with a high level of self-goal setting exert lower levels of weekly emotional exhaustion in response to intermediate levels of weekly telecommuting than employees with lower levels of self-goal setting.
4.3 Method

4.3.1 Procedure and Participants

I used a panel-study design to examine the interplay between the weekly extent of telecommuting, self-goal setting, weekly work performance and weekly emotional exhaustion. I collected the study data as part of the Konstanz Homeoffice Study (Kunze et al., 2020) by a general survey in April 2020 (t0) and five consecutive surveys in May 2020 (t1), October 2020 (t2), January 2021 (t3), June 2021 (t4) and November 2021 (t5). Respondents took part in the t1 — t5 surveys from Friday afternoon till Monday morning. The general survey assessed employees’ self-goal setting and demographic data, while the surveys t1 — t5 assessed time-variant variables (i.e., weekly extent of telecommuting, weekly work performance and weekly emotional exhaustion). Survey participants were recruited through a survey company (Respondi), which gave me access to its online panel of participants located across Germany. Within the framework of the Konstanz Homeoffice Study, Respondi\textsuperscript{2} proved to be a reliable partner for data collection.

In t0, survey participants mirrored the German working population in terms of gender structure and age distribution, based on the most recent published data from the German statistical office (Statistisches Bundesamt, 2018). Furthermore, participants were only allowed to participate in the general survey if they (a) had a working contract, and (b) were currently at least partly working from home. Respondents received incentives up to 1.00€ for each survey they filled in. The initial sample in t0 consisted of 699 participants, while the final sample consisted of 368 participants who provided 940 surveys. The majority of the participants in the final sample were male (59 percent) and their age ranged from 20 to 73 with a mean age of 46.

\textsuperscript{2}For more information on Respondi, please visit: https://www.respondi.com/
4.3.2 Measures

Self-goal setting was collected in the general survey t0, while the weekly extent of telecommuting, weekly work performance, weekly emotional exhaustion and all controls were assessed in t1 — t5.

4.3.2.1 Weekly Extent of Telecommuting

Building on prior telecommuting research (Golden & Gajendran, 2019; Golden & Veiga, 2005), the weekly extent of telecommuting was assessed by asking respondents to indicate the percentage of work time they spent telecommuting at home in a given week: “What percent of your prescribed working time did you work from home this week (M/D/YYYY)?”. Values of the weekly extent of telecommuting ranged from 0 to 100. Higher scores indicate a greater proportion of time spent working as a home-based teleworker.

4.3.2.2 Weekly Work Performance

I assessed weekly work performance using three items from an in-role performance scale developed by Williams and Anderson (1991). Following the recommendation for diary studies (Gabriel et al., 2019; Uy et al., 2010), I used a shortened version of the original scale to reduce participants fatigue and adapted the scale for week-specific assessments. Sample items were “in this week, I performed tasks that were expected of me” and “in this week, I adequately competed assigned duties”. Items were rated on a five-point scale ranging from 1 (strongly disagree) to 5 (strongly agree). Cronbach’s $\alpha$ was calculated separately for each survey and ranged from 0.91 to 0.94 ($M = 0.93$) over the surveys.

4.3.2.3 Weekly Emotional Exhaustion

I measured weekly emotional exhaustion using three items from the emotional exhaustion subscale of a German adaptation (Schermuly &
4.3. METHOD

Meyer, 2016) of the Maslach Burnout Inventory (Maslach & Jackson, 1981). I adapted the items for week-specific assessments. Sample items included “in this week, I felt emotionally drained by my work” and “in this week, I felt exhausted at the end of a working day”. Items were rated on a five-point scale ranging from 1 (strongly disagree) to 5 (strongly agree). Cronbach’s α ranged from 0.91 to 0.95 (M = 0.93) over the surveys.

4.3.2.4 Self-goal Setting

Self-goal setting was measured with three items from a German adaptation (Andreßen & Konradt, 2007) of the self-leadership scale by Houghton and Neck (2002). Sample items were “I establish specific goals for my own performance”, and “I think about the goals that I intend to achieve in the future”. Items were rated on a five-point scale ranging from 1 (strongly disagree) to 5 (strongly agree). Cronbach’s α was 0.90 in t0.

4.3.2.5 Controls

Following the classic approach to leadership, I controlled for weekly consideration and weekly initiating structure to rule out spurious relations at the within-person level which is the level of interest in the present analysis. Consideration refers to “leadership behavior that involves concern for employees’ well-being, expressions of support, and displays of warmth and approachability” (Lambert et al., 2012, p. 913), while initiating structure is defined as “leadership behavior that involves clarifying task responsibilities (of the leader and of subordinates), providing direction, and letting subordinates know what is expected of them” (Lambert et al., 2012, p. 913). Both leadership dimensions have been shown to be key determinants of employee work effectiveness (Judge et al., 2004). I measured consideration and initiating structure using three items developed by Lambert et al. (2012) respectively. I asked respondents to rate the behavior of their direct supervisor within a given week on a five-point scale ranging from 1 (never) to 5 (always). Sample items were “she/he
acted friendly and approachable” (consideration) and “she/he let me know what was expected of me” (initiating structure). Cronbach’s α for consideration ranged from 0.89 to 0.93 ($M = 0.91$) and Cronbach’s α for initiating structure ranged from 0.91 to 0.92 ($M = 0.92$) over the surveys.

### 4.3.3 Data Analysis

Given the nested data structure of my data (i.e., observations nested within individuals), I calculated the intraclass correlation coefficient (ICC1) for my criterion measures and found substantial within-person level variation suggesting non-interdependence of errors (Raudenbush & Bryk, 2010). An ICC1 of 0.34 for weekly work performance revealed that 34 percent of the variance in weekly work performance lied between individuals and 66 percent of the variance within individuals. Likewise, the ICC1 for weekly emotional exhaustion was 0.40 indicating that 40 percent of the variance in weekly emotional exhaustion lied between individuals and 60 percent within individuals. Furthermore, the within-person variance for the weekly extent of telecommuting was 65 percent (ICC1 = 0.35). Consequently, I tested all hypotheses using mixed-effect models including a random intercept for the higher-level entity (i.e., identification variable) in Stata SE16.

Since the extent of telecommuting, work performance, emotional exhaustion, consideration and initiating structure varied over time, they were treated as Level 1 (within-person) variables, and self-goal setting was treated as a Level 2 (between-person) variable in the model. Following prior recommendations (Bliese et al., 2020), I included the person mean of the independent variable (i.e., the weekly extent of telecommuting) as a predictor along with the raw independent variable to assure accurate estimation of the proposed within-person effects. Furthermore, I followed the advice by Singer and Willett (2003) and controlled for time as a continuous variable, since the predictor and the outcome might systematically change throughout the study from April 2020 to November
2021. Time was included in the fixed part of the model.

Model 1 included the weekly extent of telecommuting to control the linear contribution. Model 2 included the square of the weekly extent of telecommuting to test the curvilinear relationship between the weekly extent of telecommuting and the outcome variables. Model 3 added self-goal setting to test its main effect on the outcome variables. Finally, in Model 4, I tested the interaction of the weekly extent of telecommuting squared and self-goal setting on the outcome variables.

To fully establish the proposed quadratic relationships, I followed the three-step procedure recommended by Lind and Mehlum (2010). First, I examined whether the coefficient of the squared term of the weekly extent of telecommuting in Model 2 was significant and of the expected sign — that is positive for a u-shape and negative for an inverted u-shape. Second, I examined whether the slope was sufficiently steep at both ends of the data range. Lastly, I located the turning point within the data range.

4.4 Results

4.4.1 Descriptive Statistics

Descriptive statistics, within-person and between-person level correlations are shown in Table 4.1. On the within-person level, the extent of telecommuting significantly correlated with emotional exhaustion ($r = -0.13$, $p = 0.00$), but not with work performance ($r = -0.00$, $p = 0.90$). Performance and emotional exhaustion correlated at a moderate level ($r = -0.33$, $p = 0.00$). Both outcome variables significantly correlated with the leadership dimensions in the expected direction. On the between-person level, self-goal setting was significantly correlated with the extent of telecommuting ($r = -0.10$, $p = 0.05$) and work performance ($r = 0.15$, $p = 0.00$). Furthermore, there was significant correlation between work performance and emotional exhaustion ($r = -0.35$, $p = 0.00$). The leadership dimensions significantly correlated with work performance, emotional
exhaustion and self-goal setting in the expected direction.

4.4.2 Hypotheses Testing

Table 4.2 and Table 4.3 display the results of the hypotheses testing for weekly work performance and weekly emotional exhaustion respectively. Hypothesis 1a suggested that the within-person effect of the weekly extent of telecommuting on employees’ weekly work performance would be curvilinear in the shape of a “U”. As shown in Table 4.2, the coefficient of the squared term of the weekly extent of telecommuting was positive and significant in Model 2 (Coef. = 0.00, SE = 0.00, p = 0.00). Furthermore, the slope was sufficiently steep at both ends of the data range. In particular, the slope at the low end of the X-range was negative and significant (Coef. = -0.01, SE = 0.00, p = 0.00) and the slope at the high end of the X-range was positive and significant (Coef. = 0.01, SE = 0.00, p = 0.00). The turning point could be located at 51.71 percent of telecommuting. Figure 4.2 graphically illustrates the u-shaped effect. As hypothesized weekly work performance was highest, when employees telecommuted a little or a lot during the week, and lowest when employees telecommuted a medium amount throughout the week (i.e., 51.71 percent). Therefore, Hypothesis 1a was supported.

Hypothesis 1b proposed that the within-person effect of the weekly extent of telecommuting on employees’ weekly emotional exhaustion would be curvilinear in the shape of an inverted “U”. As shown in Table 4.3 Model 2, the coefficient of the squared term of the weekly extent of telecommuting was negative and significant (Coef. = -0.00, SE = 0.00, p = 0.05). Furthermore, the slope at the high end of the X-range was negative and significant (Coef. = -0.01, SE = 0.01, p = 0.00), but the slope at the low end of the X-range was not significant (Coef. = -0.01, SE = 0.01, p = 0.15). The turning point could be located at 31.90 percent of telecommuting. Figure 4.3 graphically illustrates the effect. The form indeed approximated an inverted u-shape. Taken together, the results revealed a
tendency for an inverted u-shaped effect, but they could not fully support it. Consequently, Hypothesis 1b is partially supported.

In the next step, I examined whether self-goal setting would act as a boundary condition in the proposed relationships. In particular, Hypothesis 2a suggested that self-goal setting would moderate the u-shaped effect of the weekly extent of telecommuting on weekly work performance. The results in Table 4.2 revealed a significant and positive direct effect of self-goal setting on work performance in Model 3 (Coef. = 0.08, SE = 0.03, p = 0.01). However, the coefficient of the cross-level interaction between the squared term of the weekly extent of telecommuting and self-goal setting was not significant in Model 4 (Coef. = -0.00, SE = 0.00, p = 0.87). Thus, Hypothesis 2a was not supported.

Lastly, Hypothesis 2b proposed that self-goal setting would moderate the inverted u-shaped effect of the weekly extent of telecommuting on weekly emotional exhaustion. As Table 4.3 Model 3 and 4 indicate, neither the direct effect of self-goal setting on emotional exhaustion (Coef. = -0.01, SE = -0.05, p = 0.89) nor the cross-level interaction between the squared term of the weekly extent of telecommuting and self-goal setting (Coef. = -0.00, SE = 0.00, p = 0.27) were significant. Therefore, Hypothesis 2b was not supported.
Table 4.1: Means, Standard Deviations, and Correlations of Study Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extent of telecommuting</td>
<td>66.92</td>
<td>28.73</td>
<td>-0.13***</td>
<td>-0.00</td>
<td>0.04</td>
<td>0.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work performance</td>
<td>4.37</td>
<td>0.61</td>
<td>0.09</td>
<td>-0.33***</td>
<td>0.21***</td>
<td>0.14***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Emotional exhaustion</td>
<td>2.38</td>
<td>0.93</td>
<td>0.05</td>
<td>-0.35***</td>
<td>-0.20***</td>
<td>-0.13***</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
| Self-goal setting | 3.78 | 0.87 | -0.10* | 0.15** | -0.06 | -
| Consideration | 3.72 | 0.85 | -0.08 | 0.31*** | -0.26*** | 0.13** |
| Initiation structure | 3.46 | 0.93 | -0.09 | 0.23*** | -0.16** | 0.25*** |

Note. Correlations above the diagonal are within-person correlations (N = 940). Correlations below the diagonal are between-person correlations. Means and standard deviations (SD) were computed at the between-person level of analysis. Level 1 variables were aggregated to the between-person level prior to computing between-person correlations. Because nesting of observations in persons is not accounted for significance, values for within-person correlations should be interpreted with caution. * p \(\leq 0.05\) (two-tailed); ** p \(\leq 0.01\) (two-tailed); *** p \(\leq 0.001\) (two-tailed).
Table 4.2: Multilevel Model predicting Within-person Weekly Work Performance

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>SE</td>
<td>p</td>
<td>B</td>
</tr>
<tr>
<td>Intercept</td>
<td>3.52</td>
<td>0.11</td>
<td>0.00</td>
<td>3.73</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td>0.04</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>Consideration</td>
<td>0.19</td>
<td>0.03</td>
<td>0.00</td>
<td>0.19</td>
</tr>
<tr>
<td>Initiating structure</td>
<td>0.01</td>
<td>0.03</td>
<td>0.79</td>
<td>0.01</td>
</tr>
<tr>
<td>Telecommuting pmean</td>
<td>0.00</td>
<td>0.00</td>
<td>0.34</td>
<td>0.00</td>
</tr>
<tr>
<td>Main effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Telecommuting</td>
<td>0.00</td>
<td>0.00</td>
<td>0.69</td>
<td>-0.01</td>
</tr>
<tr>
<td>Telecommuting$^2$</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Self-goal</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interaction terms</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Telecommuting × self − goal</td>
<td>-0.00</td>
<td>0.00</td>
<td>0.74</td>
<td></td>
</tr>
<tr>
<td>telecommuting$^2$ × self − goal</td>
<td>-0.00</td>
<td>0.00</td>
<td>0.87</td>
<td></td>
</tr>
<tr>
<td>Number of parameters</td>
<td>8</td>
<td></td>
<td></td>
<td>9</td>
</tr>
<tr>
<td>-2 log likelihood</td>
<td>-964.26</td>
<td></td>
<td></td>
<td>-947.65</td>
</tr>
<tr>
<td>AIC</td>
<td>1944.51</td>
<td></td>
<td></td>
<td>1913.29</td>
</tr>
</tbody>
</table>

Note. N = 940 at the within-person level and N = 368 at the between-person level. Time is included as a continuous variable into the regression analysis and modeled as fixed effect. Unstandardized effects are reported. Telecommuting = weekly extent of telecommuting, telecommuting pmean = person mean of the weekly extent of telecommuting, self-goal = self-goal setting.
**Table 4.3: Multilevel Model predicting Within-person Weekly Emotional Exhaustion**

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>SE</td>
<td>p</td>
<td>B</td>
</tr>
<tr>
<td>Intercept</td>
<td>3.33</td>
<td>0.18</td>
<td>0.00</td>
<td>3.21</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td>0.00</td>
<td>0.02</td>
<td>0.85</td>
<td>0.01</td>
</tr>
<tr>
<td>Consideration</td>
<td>-0.27</td>
<td>0.05</td>
<td>0.00</td>
<td>-0.26</td>
</tr>
<tr>
<td>Initiating Structure</td>
<td>0.01</td>
<td>0.04</td>
<td>0.76</td>
<td>0.01</td>
</tr>
<tr>
<td>Telecommuting pmean</td>
<td>0.00</td>
<td>0.00</td>
<td>0.13</td>
<td>0.00</td>
</tr>
<tr>
<td>Main Effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Telecommuting</td>
<td>-0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>-0.00</td>
</tr>
<tr>
<td>Telecommuting</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-goal</td>
<td>-0.01</td>
<td>-0.05</td>
<td>0.89</td>
<td>-0.26</td>
</tr>
<tr>
<td>Interaction Terms</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Telecommuting × Self-goal</td>
<td>0.01</td>
<td>0.00</td>
<td>0.09</td>
<td>0.00</td>
</tr>
<tr>
<td>Telecommuting × Telecommuting</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-goal × Telecommuting</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Number of parameters: 8

-2 log likelihood: 2784.49

AIC: 2784.49

Note: N = 940 at the within-person level and N = 368 at the between-person level. Time is included as a continuous variable into the regression analyses, and controls for individual differences in self-goal setting.
4.4. RESULTS

Figure 4.2: Curvilinear Effect of the Weekly Extent of Telecommuting on Weekly Work Performance

Figure 4.3: Curvilinear Effect of the Weekly Extent of Telecommuting on Weekly Emotional Exhaustion
4.5 Discussion

The goal of the study was to explore the within-person variance in employees’ work effectiveness, as reflected in work performance and emotional exhaustion, when employees telecommute at varying levels throughout the week. In line with the conceptual ideas of COR theory (Hobfoll, 1988, 1989, 2001), I proposed the within-person effect of the weekly extent of telecommuting on employees’ weekly work effectiveness to be curvilinear. In particular, I proposed the effect to be u-shaped for the relationship between the extent of telecommuting and work performance and inversely u-shaped for the relationship between the extent of telecommuting and emotional exhaustion.

Indeed, my analyses could provide support for a u-shaped effect of the weekly extent of telecommuting on weekly work performance. However, the size of the effect was small, since the extent of telecommuting ranged from 0 to 100. Yet a closer look at the graphical illustration of the effect reveals that the result does provide meaningful implications for employee performance. As displayed in Figure 4.2, employees’ level of weekly work performance initially declined from about 4.55 to 4.20 as the weekly extent of telecommuting increased from 0 to 52 percent. Yet employees were able to recover and increase their level of weekly work performance to 4.51 as they increased their amount of telecommuting from 52 to 100 percent. Thus, telecommuting at a low or a high level compared to telecommuting at an intermediate level corresponds to a difference in performance of roughly 7 percent. This finding suggests that resource-enhancing ways of working are either working predominately at the office or working predominately remotely throughout the week, while a hybrid way of working, in which employees tend to switch regularly between work locations may take a toll on employees’ resources and, thus on their work performance.

Furthermore, the results provided indications for an inversely u-shaped effect of the weekly extent of telecommuting on emotional exhaustion.
First, the squared term of the weekly extent of telecommuting on weekly work performance was significant and negative. Second, the slope at the high end of the telecommuting range past the turning point of 32 percent was negative and significant and, lastly, the form of the effect approximated an inverted u-shape as it can be seen in Figure 4.3. Yet the slope was not sufficiently steep at the low end of the telecommuting-range. At low levels of weekly telecommuting, employees experienced already a medium level of emotional exhaustion. A possible reason might be related to the time frame of my data collection. The data for this study were collected during the COVID-19 pandemic from its start in April 2020 to November 2021. Since the COVID-19 virus is mainly transmitted via social contact (World Health Organization, 2020a), working predominately at the office is likely to have increased the risk of contracting the virus. This increased illness susceptibility might have sapped the emotional stamina of employees causing feelings of emotional exhaustion at low levels of weekly telecommuting. Indicative for this reason is that employees’ level of emotional exhaustion significantly decreased from 2.55 to 2.23 which corresponds to a drop in emotional exhaustion of 12.55 percent as the level of telecommuting rose past the turning point of 32 percent to 100 percent. This sharp decline in emotional exhaustion suggests that telecommuting at extensive levels might have been a relief to employees given the extraordinary circumstances of the pandemic. Considering these mixed findings, future research is encouraged to reassess the possibility of an inverted u-shaped effect of the weekly extent of telecommuting on weekly emotional exhaustion when the pandemic situation has improved.

Lastly, I shed light on the telecommuting-effectiveness link by investigating a potential cross-level moderator of this relationship (i.e., self-goal setting). While the study findings showed a positive direct effect of self-goal setting on weekly work performance, they did not support a moderation effect of self-goal setting in the relationship between the weekly extent of telecommuting and both outcomes. A possible explanation might be that effective self-regulation may require more than setting
goals given today’s fast-paced work environment. Considering that goals might quickly become obsolete because customers change their minds or a supervisor needs support urgently, sticking to goals might impair flexibility. Moreover, the rapidly changing demands might make the original goal impossible to achieve at the moment. Therefore, employees may also need to actively engage in weekly goal adaption (König et al., 2010). Weekly goal adaption might enable employees to reprioritize or postpone their goals and to change the level of effort toward their goals (König et al., 2010) which might, in turn, have implications for the extent to which employees can telecommute during the week. For example, consider a customer who has asked a team to deliver their product sooner. Hence, team members will likely reprioritize their goals for the coming days to meet the earlier deadline. Since they may need to coordinate more closely and collaborate within the team to complete the product, team members will likely postpone their telecommuting time and prefer to work in the office. The example shows that adapting goals can indeed have an effect on the extent of telecommuting. Therefore, exploring self-regulation in terms of goal adaption as a potential moderator in the relationship between the weekly extent of telecommuting and weekly work effectiveness may be a promising avenue for future research. In the following, theoretical and practical implications as well as limitations of the present study are discussed.

4.5.1 Theoretical Implications

The present study contributes to the literature on telecommuting by corroborating and extending prior findings in several ways. First, the present study extents research on the relationship between telecommuting and employee outcomes at a within-person level (Anderson et al., 2015; Biron & van Veldhoven, 2016; Delanoeije & Verbruggen, 2020; Vega et al., 2015). Measuring telecommuting by asking respondents to indicate the percentage of work time spent telecommuting in a given week goes beyond
the dichotomous measurement approach used previously. In this way, I was able to capture nuances in the telecommuting variance which presumably makes the measurement more realistic given the variety of how telecommuting is applied. Furthermore, I collected data over 1.5 years and was, thus, able to examine the long-term effect of telecommuting on employees’ work effectiveness. As a result, my results differ from previous findings regarding the within-person effect of telecommuting on employee outcomes. Specifically, my findings challenge the view that employees generally have a more positive work experience while telecommuting (Anderson et al., 2015; Biron & van Veldhoven, 2016; Delanoeije & Verbruggen, 2020; Vega et al., 2015). The study results showed that employees experienced enhanced work performance, but only when they telecommuted very little or very much during the week. At intermediate levels of telecommuting when employees switch regularly between work locations during the week, employees’ level of weekly work performance dropped by 7 percent and was, thus, considerably lower. Therefore, the present study might provide a more fine-grained view of the relationship between the extent of telecommuting and work performance at the within-person level.

Second, the study findings add to the literature proposing the impact of telecommuting on employee outcomes to be curvilinear and, thus, to be more complex than previously thought (Golden, 2006b; Golden & Veiga, 2005). Interestingly, Golden and Veiga (2005) and Golden (2006b) found an inverted u-shaped relationship between the extent of telecommuting and job satisfaction indicating that, on average, employees are most satisfied with their work at relatively moderate levels of telecommuting. Furthermore, calling for more research on the relationship between the extent of telecommuting and employee performance, Golden and Veiga (2005) expected increased levels of performance at moderate levels of telecommuting paralleling their findings on job satisfaction. However, results of the present study support a u-shaped within-person relationship between the weekly extent of telecommuting and weekly work performance. The difference in results and expectations can be explained by the differ-
ent level of analysis. Previous studies (Golden, 2006b; Golden & Veiga, 2005) assessed the relationship between the extent of telecommuting and job satisfaction at the between-person level, while the present study had a within-person focus. A substantial body of research has demonstrated that established relationships between constructs can change in magnitude or even direction when examined at a different level of analysis (Curran & Bauer, 2011; Hoffman & Stawski, 2009; Zhang & Wang, 2014). Therefore, future research is encouraged to further explore the possibility that the curvilinear impact of the extent of telecommuting on employee outcomes changes in direction at different levels of analysis.

Lastly, the study results corroborate the literature proposing extensive telecommuting to be a valuable resource that protects employees from feelings of being emotionally overextended (Golden, 2006a; Sardeshmukh et al., 2012). The analysis demonstrated that employees’ level of emotional exhaustion declined by roughly 12 percent as employees’ extent of telecommuting rose past the turning point of 32 percent to 100 percent. This finding suggests that high levels of telecommuting can play a critical role in protecting workers’ mental health, especially during extraordinary times like the COVID-19 pandemic.

4.5.2 Limitations and Future Research

Despite multiple strengths, such as a repeated measurement design over six time points, my research also has limitations that should be considered when interpreting the results. First, I assessed work performance and emotional exhaustion by self-reports which raises questions regarding potential social desirability or self-serving biases. However, I took measures when designing the study and analyzing the data to minimize such biases. The focus of the present study was on the weekly variation in weekly work effectiveness within persons and not on between-person differences (i.e., on the absolute level of work effectiveness). Biases, such as the self-serving bias, should influence the absolute level of work effec-
tiveness and should further be attributable to between-person variation, but not to within-person variation (Binnewies et al., 2009).

Second, all measures are based on self-reports of the same person which raises concerns about common method variance (Podsakoff et al., 2003). However, Siemsen et al. (2010) demonstrate that quadratic and interaction effects cannot be artificially created through common method variance. To the contrary, common method variance usually causes these nonlinear effects to be deflated, making them more difficult to detect through statistical means. Therefore, I am positive, that common method variance did not invalidate my empirical findings.

Third, I explained the differences in weekly work effectiveness by arguing that employees experience resource gains and losses depending on their weekly extent of telecommuting. However, I did not directly measure the mediating process of resource gains or losses. Therefore, studies investigating mediating mechanisms in the relationship between the weekly extent of telecommuting and weekly work effectiveness would be useful.

### 4.5.3 Practical Implications

The COVID-19 pandemic has made telecommuting the “new normal” which has sparked a discussion about what a post-pandemic workplace might look like. Employees appear to prefer a hybrid way of working (Bloom, 2020), while many employers seem to be reluctant to implement a long-term telecommuting strategy (Flint, 2020; Thomas & Cutter, 2021). These different points of view show that negotiating and crafting a post-pandemic future of work remains a major challenge for HR managers, leaders and employees. Providing insights into the relationship between telecommuting and employee work effectiveness over time, the present study, may, therefore, provide relevant and timely implications for practitioners.

Building on the current discussion whether organizations should generally call back their employees into the office (O’Conner, 2021), organi-
izations are encouraged to allow their employees to work extensively in a remote form in the future. The study findings demonstrated that employees show a high level of weekly work performance when they telecommute very little or very much during the week. Furthermore, for reaching a peak state of performance, employees are recommended to not waste their resources by constantly switching between work locations throughout the week, but to decide on one location per week where they would like to predominantly perform their work.

4.6 Conclusion

The present study explored the within-person variance in employees’ work effectiveness, as reflected in the level of weekly work performance and weekly emotional exhaustion, when employees work at varying levels of telecommuting throughout the week. Results supported that the impact of the weekly extent of telecommuting on employees’ weekly work performance was curvilinear in the shape of a “U”. Put differently, employees performed best when they telecommuted only a little or a lot, but they appeared to lose 7 percent of their work performance when they telecommuted at an intermediate level (i.e., 52 percent). Furthermore, the results provided indications for an inversely u-shaped effect of the weekly extent of telecommuting on emotional exhaustion. Taken together, the findings indicate that resource-enhancing ways of working are either working predominantly at the office or working predominantly remotely throughout the week, while a hybrid way of working, in which employees tend to switch regularly between work locations, may take a toll on employees’ resources and, thus on their work effectiveness.
5.1 Summary and Integration

The intertwined and mutually reinforcing workplace dynamics of the digitalization, the COVID-19 pandemic, and the flexibilization of the location of work in the form of telecommuting have kept the world of work on its toes and substantially altered the individual experience of work. Much research has been devoted to the consequences of these workplace dynamics on employees. Yet several ambiguities and inconsistencies still exist precluding a better understanding of employees’ adaptive responses to the organizational change driven by the digitalization, the COVID-19 pandemic, and telecommuting. Aiming to resolve the inconsistent findings from past research, I conducted three empirical studies — each focusing on one of the workplace dynamics.

In Study 1, my co-author, Florian Kunze, and I attempted to advance our understanding of employees’ adaptive response to the digitalization. Research Question 1 inquired about the true nature of digital competence. By integrating Campbell et al.’s (1993) performance model with the growing body of digital workplace literature (Agarwal et al., 2000; Downey & Rainer, 2009; Teo, 2009), we conceptualized employees’ digital fluency, which consists of digital knowledge and digital self-efficacy, as a
new person-specific predictor of digital work performance. Furthermore, we built on social learning theory (Bandura, 1977) to suggest that leaders’ and coworkers’ digital fluency act as moderators in the relationship between employees’ digital fluency and their digital work performance. We found support for the positive effect of employees’ digital fluency on their digital work performance and the moderating effect of leaders’ digital fluency in a multi-source and time-lagged sample of 218 employees and 17 leaders from a medium-sized German technology company. Therefore, Florian Kunze and I were able to contribute to clarifying the concept of digital competence in several ways. We provided a theoretical conceptualization and empirical validation of digital fluency as a higher-order construct based on two distinctive dimensions. Thus, our study corroborated research (Oberländer et al., 2020; Y. Wang & Haggerty, 2009, 2011) that defines digital competence as a multidimensional construct combining a novel ensemble of knowledge, skills, abilities, and other characteristics. Furthermore, by considering digital fluency in a work setting and demonstrating its relevance for employees’ digital work performance, our research broadened the understanding of the concept of digital competence at work — a context that has largely been neglected by prior research (Oberländer et al., 2020).

Study 2 focused on employees’ response to the COVID-19 pandemic. Research Question 2 inquired about critical contingencies that either predispose to or protect employees from the psychological distress caused by the COVID-19 pandemic. Building on the COR theory (Hobfoll, 1988, 1989), I argued that surging COVID-19 cases have the potential to be psychologically and physically draining and, thus, positively affect employees’ emotional exhaustion. Furthermore, I assumed that employees’ age and extent of working from home are key context factors that influence employees’ strain reaction to the daily COVID-19 surge. I tested the proposed relationships based on an eight-day diary study with largely a representative data set of the German workforce with 389 participants, which was integrated with official COVID-19 case statistics on the county
level. However, my analyses could not provide support for the hypotheses. Contrary to my expectation, my research revealed a significant negative effect of age on daily emotional exhaustion. Still, Study 2 contributed to COVID-19 research by corroborating recent research by Kimhi et al. (2020) showing that older age predicts lower levels of sense of danger and distress symptoms. Furthermore, Study 2 reaffirmed the strand of literature highlighting older workers’ ability to maintain well-being on days with high-intensity negative events (Scheibe, 2021; Scheibe & Moghimi, 2021).

In Study 3, I considered employees’ adaptive response to the flexibilization of the location of work in the form of telecommuting. Guided by Research Question 3, I explored whether employees’ weekly effectiveness waxes and wanes over time as a function of the amount of telecommuting during a workweek. Building on COR theory (Hobfoll, 1988, 1989), I suggested that the within-person effect of the weekly extent of telecommuting on employees’ weekly effectiveness, as reflected in their weekly work performance and weekly emotional exhaustion, is curvilinear. More specifically, I proposed the effect to be u-shaped for the relationship between the extent of telecommuting and work performance and inversely u-shaped for the relationship between the extent of telecommuting and emotional exhaustion. I further explored the moderating role of self-goal setting in these relationships. Results from a panel study of 368 German employees conducted over 1.5 years fully supported the u-shaped within-person effect of the weekly extent of telecommuting on employees’ weekly work performance and further provided indications for an inversely u-shaped effect of the weekly extent of telecommuting on emotional exhaustion. Therefore, I was able to contribute to the telecommuting literature in several ways. My findings provided a new perspective on the long-term effect of telecommuting at the within-person level, challenging the view that employees generally have more positive work experience while telecommuting (Anderson et al., 2015; Biron & van Veldhoven, 2016; Delanoeije & Verbruggen, 2020; Vega et al., 2015). Furthermore, my findings added
to the literature proposing the impact of telecommuting on employee outcomes to be curvilinear and, thus, to be more complex than previously thought (Golden, 2006b; Golden & Veiga, 2005). Lastly, the study results corroborated the literature proposing extensive telecommuting to be a valuable resource that protects employees from feelings of being emotionally overextended (Golden, 2006a; Sardeshmukh et al., 2012).

By integrating the research findings of the three studies, the dissertation provides two main contributions to the literature. First, my work enriches the literature on employees’ reaction to exponential change in organizations (Oreg et al., 2011). I offer a collective view on employees’ adjustment to the organizational change driven by the digitalization, the COVID-19 pandemic and the flexibilization of the location of work in the form of telecommuting — three workplace dynamics that are very different in nature, but collectively have triggered a fundamental organizational change that has substantially altered individual and organizational functioning. In doing so, I explore employees’ adaption to organizational change from different theoretical perspectives using different methodological approaches. In Study 1, I take a competence-based view to examine interindividual differences in employees’ digital work performance, while in Study 2 and Study 3, I adopt a resource-based view to investigate intraindividual differences in employees’ work performance and emotional exhaustion. This dissertation, therefore, contributes to a holistic understanding of employees’ reaction to fundamental organizational change.

Second, my work contributes to the person-centric work psychology research which focuses on the subjective nature of work experience (S. Liu et al., 2011; Weiss & Rupp, 2011). In all three studies, I adopt the perspective that the fundamental transformation of the world of work is ultimately a personal one, and thus focus on individual employees and their adaptive response to the digitalization, the CODIV-19 pandemic and telecommuting. Study 2 and Study 3 in particular contribute to advancing the person-centric work psychology literature as they respond
5.2. OVERALL LIMITATIONS AND AVENUES FOR FUTURE RESEARCH

5.2 Overall Limitations and Avenues for Future Research

Beyond the specific limitations of each study (see subsection 2.4.2, subsection 3.5.2, and subsection 4.5.2), some limitations are more general.

First, the ability to draw causal conclusions is limited in all three studies. In all three studies, I assumed causal effects between the variables of interest. For example, in Study 1, employees’ digital fluency was assumed to positively influence their digital work performance. However, testing such effects in a strictly causal manner requires an exogenous manipulation of the predictor and thus, experimental methods, such as a randomized experiment (Morgan & Winship, 2007). Yet, in all three studies, the randomization of the independent variables was not feasible in the field settings under study which raises questions about endogeneity (i.e., omitted variables, omitted selection, simultaneity, measurement error) and, therefore, about the causal interpretation of results (Antonakis et al., 2010). However, seeking to reduce endogeneity concerns, I relied on convincing theoretical arguments for the causal ordering of the relations and further used a time-lagged design in Study 1 and longitudinal designs in Study 2 and 3. Still, future research is encouraged to go beyond observational data and use experimental data to infer causality regarding the direction of the proposed relationships.

Second, the cultural generalization of the research findings appears to be limited as only samples from western countries (i.e., Germany, USA) were used in all three studies to test the hypothesized relationships. Although this dissertation did not aim to be culturally comparative, the possibility that the research findings of the present dissertation may be dif-
Different in other cultural contexts, such as collectivist cultures (e.g., China) cannot be ruled out. Therefore, a fruitful avenue for future research is to explore employees’ adjustment to the digitalization, the COVID-19 pandemic and telecommuting using other cultural samples and ideally a cross-cultural approach. Examining the dynamics from different cultural perspectives could provide interesting insights, as the impact strength of the workplace dynamics may vary depending on the cultural context. For example, the digital transformation is already very advanced in Asian countries (Tonby et al., 2020). People’s lives in Asia are strongly based on technology which has penetrated all aspects of their daily activities far more deeply than in many other parts of the world. Thus, employees’ adjustment to the digital workplace might already assume much greater importance in Asia than in western countries.

Third, Study 2 and Study 3 partially contain the same participants as both studies are based on data that were collected as part of the Konstanz Homeoffice Study (Kunze et al., 2020). However, Study 2 and Study 3 use different data time points. While Study 2 is based on an eight-day diary study from March 31 to April 9, 2020, Study 3 draws information from the general survey in March 2020 and the five survey waves from May 2020 to November 2021.

Forth, my dissertation is based on survey research, in which the main research strategy is to ask respondents to rate statements about the variables of interest. Considering that the central dependent variables in this work are performance and emotional exhaustion, social desirability bias or self-serving bias could be have influenced the results. Respondents might have felt the tendency to overrate their performance and deny their emotional exhaustion because success at work is highly valued in society, while feelings of weakness are socially undesirable. However, I took measures when designing the studies and analyzing the data to minimize such biases. In Study 1, performance was measured not by the employees themselves, but by their respective supervisor. Furthermore, Study 2
and Study 3 used a within-person study design which focuses on the variation in performance and emotional exhaustion within persons and not on between-person differences (i.e., on the absolute level of performance and emotional exhaustion). Biases, such as the self-serving bias, should influence the absolute level of performance or emotional exhaustion and should further be attributable to between-person variation, but not to within-person variation (Binnewies et al., 2009).

Lastly, the studies were in part limited in their ability to test the mechanisms underlying the observed effects. While the theoretical arguments in Study 2 and Study 3 were specific about the mechanisms underlying the predictor-outcome relationship, I was not able to directly test the proposed mechanisms. In Study 2 and Study 3, I argued that the impact of the respective workplace dynamic on employees can be explained by resource gains or resources losses. However, strict space restrictions in the data collection process precluded a direct test of the mechanism. Accordingly, I encourage future research to extend Study 2 and Study 3 by directly measuring the underlying theoretical mechanisms.

Apart from the limitations, the findings of the dissertation offer several avenues for future research. One opportunity for future research is to explore the moderating role of digital fluency in the holistic technostress process (Benlian, 2020; Califf et al., 2020). Digital fluency might act as a moderator either in the appraisal process through which employees appraise the environmental conditions or in the decision process through which employees decide how to respond either positively or negatively to the appraised stressor. Considering the appraisal process, digitally fluent employees might appraise technology-related demands as challenge-stressors that can promote their personal growth and achievement, while employees with low levels of digital fluency might perceive such demands as hindrance stressors that limit their personal development and accomplishments. The same pattern could apply to the decision process. High levels of digital fluency might enable employees to respond positively to
the appraised technology stressor as indicated by the presence of positive psychological states. In contrast, low levels of digital fluency might lead to a negative response in the form of negative psychological states among employees.

Organizational behavior research should devote more attention to understanding the negative spillover of disruptive and traumatic events into the workplace, considering the high frequency with which such events tend to occur (James, 2011). Future research is recommended to particularly focus on critical contingencies that could mitigate the cross-level effect of extra-organizational stressors on individual-level outcomes. A moderator that might be worthwhile to explore in stressor-strain relationships is age diversity in teams. Study 2 revealed that aging employees experience significantly lower levels of daily emotional exhaustion as response to the COVID-19 surge. In this vein, past research indicates that aging employees compared to younger employees use more adaptive emotion-regulation strategies and less maladaptive strategies (Dahling & Perez, 2010; Hertel et al., 2015; Scheibe et al., 2016). Thus, building on social learning theory (Bandura, 1977), older employees in an age-diverse team might act as role models to younger employees, showing them how to better maintain emotional functioning during a crisis.

A fruitful extension for telecommuting research would be to explore boundary conditions in the relationship between a hybrid work practice and employee effectiveness. Current discussions of a post-pandemic future of work indicate that hybrid work practices are here to stay (Choudhury, 2020; Lufkin, 2022). Yet the findings of Study 3 suggest that employees perform worst when they work in a hybrid form and switch regularly between work locations throughout the week. Identifying factors that help employees maintain their effectiveness when working in a hybrid form may, therefore, provide timely and relevant implications. Potential moderators in the relationship between an intermediate level of telecommuting and employee effectiveness could be factors that enhance employees’
5.3 Practical Implications

Experts are certain that the future of work will be characterized by extensively digital and remote work practices (World Economic Forum, 2020). Yet the path to this future still appears to present companies and
employees with two major challenges. The first vital problem seems to be that technological skills are a bottleneck. Skill shortages seem to prevent organizations from realizing the growth potential of new technological advancements and expose employees to the risk of job displacement (World Economic Forum, 2020). The second challenge appears to be that employers and employees have conflicting views on the implementation of a long-term telecommuting strategy in the wake of the pandemic. While employees appear to welcome a flexible, hybrid way of working (Bloom, 2020), employers seem to be reluctant towards telecommuting due to productivity concerns (Flint, 2020; Thomas & Cutter, 2021). Addressing these two key challenges, the present dissertation may provide relevant and timely implications for practitioners to shape the future of work.

In Study 1, my co-author, Florian Kunze, and I introduced a competence that enables employees to effectively perform in a digitalized work environment: digital fluency which consists of digital knowledge and digital self-efficacy. The findings of Study 1 suggest that employees’ digital fluency shapes their digital work performance, a positive effect that can even be enhanced by modeling leaders who themselves have a high level of digital fluency. Organizations are, therefore, recommended to offer a structured training program to promote digital fluency among employees and leaders. On the one hand, such interventions should aim to deepen employees’ digital knowledge by providing employees with insights into what to do with digital technologies, how to do it and when it makes sense to use them. On the other hand, these interventions should also strengthen employees’ digital self-efficacy by providing them with mastery experiences to inspire and reinforce the feeling “I have what it takes to succeed” (Bandura, 1986; Stajkovic & Luthans, 1998).

Leaders can have a powerful impact on the process of increasing employees’ digital fluency, and, thus, need to be adequately prepared. Our results showed that digitally fluent leaders are attractive role models to their followers. In addition, leaders can focus on their followers’ appraisal
of digital self-efficacy by instilling confidence in them to build employees’ belief in their competence. Expressing a faith in followers’ digital fluency may be particularly relevant in times when employees face performance challenges and question their personal efficaciousness (Stajkovic & Luthans, 1998).

Study 3 explored effective ways of working in the context of telecommuting. Findings suggest that employees perform best when they work primarily at the office or telecommute predominately throughout the week, while they perform worst when they work in a hybrid form and regularly switch between work locations during the week. Organizations are, therefore, encouraged to implement a long-term telecommuting strategy which allows employees to work extensively in a remote form in the future. Furthermore, for reaching a peak state of performance, employees are recommended to not waste their resources by constantly switching between work locations throughout the week, but to decide on one location per week where they would like to predominantly perform their work.

In sum, to pave the way into a digital and remote future of work, my key recommendations for organizations are: (1) conduct trainings to promote digital fluency among employees and leaders, (2) enable telecommuting at extensive levels, and (3) avoid switching between work locations throughout the week.

5.4 Overall Conclusion

The mutually reinforcing and intertwined workplace dynamics of the digitalization, the COVID-19 pandemic, and the flexibilization of the location of work in the form of telecommuting have led to a wholesale shift in employees’ working practices with new demands and profoundly changing conditions. This dissertation offers new knowledge about employees’ adaptive responses to this transformational change in organizations. I hope this dissertation helps shape a future of work that creates a new, yet
good, normal for employees and motivates other scholars to gain further insights into this intriguing topic.
Appendix Chapter 2

Digital Fluency – A Key Employee Resource to Perform in the Digital Age?
A.1 Further Measurement Information

Appendix A.1 provides further information on the measurement of the constructs assessed in the MTurk sample of Study 1 (cf., chapter 2). Unless otherwise noted, 5-point Likert-type scales (1 = strongly disagree, 5 = strongly agree) were used for all measures. All items were coded such that higher scores indicate higher levels of the construct.

Following the recommendations by Hoyle and Panter (1995), we evaluated model fit by using several fit indices, including the chi-square, Comparative Fit Index (CFI), Incremental Fit Index (IFI), Tucker-Lewis-Index (TLI), and the Standardized Root Mean Square Residual (SRMR). The three incremental fit indices (CFI, IFI, TLI) appear apt for assessing the overall model fit as they have been highlighted to perform best, especially under the condition of small sample sizes (n < 250) (McDonald & Marsh, 1990; Sharma et al., 2005). CFI, IFI, and TLI values range from zero to one, with values close to 0.95 indicating superior fit (L.-t. Hu & Bentler, 1999). The SRMR was additionally taken into consideration as it has been recognized as informative and common index in CFA (Byrne, 2010). The acceptable cut-off value for the SRMR was set at < 0.08 (L.-t. Hu & Bentler, 1999).

If CFA results indicated insufficient model fit, we applied Cheng’s (2001) approach of incremental modification. Guided by standardized regression weights, high error correlations with other items and high modification indices, we identified items to exclude to achieve the best fitting measurement model. The items were deleted one by one in order to control whether dropping one measure might simultaneously affect other parts of the model (Segars & Grover, 1993).
A.1.1 Measures

A.1.1.1 Resistance to Change

Resistance to change was assessed by using the 17-item scale developed by Oreg (2003) in T1. The exact wording of the items together with their descriptive statistics is provided in Table A.1. Two items were reversed and, therefore, measured on a 5-point Likert-type scale ranging from very strong agreement (1) to very strong disagreement (5). The internal consistency of resistance to change was acceptable ($\alpha = 0.90$, $\omega = 0.91$). The results of the CFA revealed insufficient model fit ($\chi^2 = 235.51; df = 115; \chi^2/df = 2.05; CFI = 0.89; IFI = 0.89; TLI = 0.87; SRMR = 0.11$). The measurement model was defined as a hierarchical factor model, specifying resistance to change as a second-order factor and routine seeking, emotional reaction, short term focus and cognitive rigidity as first-order factors. We excluded two items which are indicated in Table A.1. Thus, the model could be continuously revised until acceptable model fit properties were attained ($\chi^2 = 144.00, df = 86; \chi^2/df = 1.67; CFI = 0.94; IFI = 0.94; TLI = 0.93; SRMR = 0.08$). Reliability estimates improved ($\alpha = 0.92$, $\omega = 0.92$).

A.1.1.2 Locus of Control

We measured locus of control by using the 24-item scale developed by Levenson (1973) in T1. The exact wording of the items together with their descriptive statistics is provided in Table A.2 and Table A.3. The internal consistency of locus of control was acceptable ($\alpha = 0.88$, $\omega = 0.89$). The overall model fit was not optimal ($\chi^2 = 375.77, df = 249; \chi^2/df = 1.51; CFI = 0.90; IFI = 0.90; TLI = 0.89; SRMR = 0.09$). The measurement model was defined as a hierarchical factor model, specifying locus of control as a second-order factor and internality, external orientation and belief in powerful others as first-order factors. We deleted one item and achieved acceptable model fit properties ($\chi^2 = 330.03, df = 227; \chi^2/df = 1.45; CFI$
= 0.92; IFI = 0.92; TLI = 0.91; SRMR = 0.07). Reliability estimates remained at an acceptable level ($\alpha = 0.88$, $\omega = 0.90$).

### A.1.1.3 General Self-efficacy

General self-efficacy was captured by using the 8-item scale by Chen et al. (2001) in T1. The exact wording of the items together with their descriptive statistics is provided in Table A.4. The internal consistency of general self-efficacy was acceptable ($\alpha = 0.92$, $\omega = 0.93$). CFA results indicated superior model fit ($\chi^2 = 24.67$, $df = 20$; $\chi^2/df = 1.23$; $CFI = 0.99$; $IFI = 0.99$; $TLI = 0.99$; $SRMR = 0.03$).

### A.1.1.4 Computer Self-efficacy

We assessed computer self-efficacy by using the 10-item scale by Compeau and Higgins (1995) in T1. Respondents were asked to indicate their level of confidence to complete their job using a new technology on a 5-point Likert-type scale (1 = not at all confident; 5 = extremely confident). The exact wording of the items together with their descriptive statistics is provided in Table A.5. The internal consistency of computer self-efficacy was acceptable ($\alpha = 0.88$, $\omega = 0.88$). CFA results indicated insufficient model fit ($\chi^2 = 88.16$, $df = 35$; $\chi^2/df = 2.52$; $CFI = 0.87$; $IFI = 0.88$; $TLI = 0.84$; $SRMR = 0.08$). We excluded two items which are indicated in Table A.5 and, thus, attained acceptable model fit properties ($\chi^2 = 34.39$, $df = 20$; $\chi^2/df = 1.72$; $CFI = 0.96$; $IFI = 0.96$; $TLI = 0.94$; $SRMR = 0.05$). Reliability estimates remained at an acceptable level ($\alpha = 0.87$, $\omega = 0.87$).

### A.1.1.5 In-role Performance

In-role performance was measured by using the 7-item scale by Williams and Anderson (1991) in T2. The exact wording of the items together with their descriptive statistics is provided in Table A.6. The internal consistency of in-role performance was acceptable ($\alpha = 0.80$, $\omega = 0.81$).
CFA results indicated insufficient model fit ($\chi^2 = 132.40$, df = 14; $\chi^2$/df = 9.46; CFI = 0.68; IFI = 0.69; TLI = 0.53; SRMR = 0.12). Therefore, two items were excluded as indicated in Table A.6 and acceptable model fit properties were attained ($\chi^2 = 10.12$, df = 5; $\chi^2$/df = 2.02; CFI = 0.97; IFI = 0.97; TLI = 0.95; SRMR = 0.04). Reliability estimates remained at an acceptable level ($\alpha = 0.77$, $\omega = 0.77$).

A.1.1.6 Digital Productivity

We assessed digital productivity by using an adapted version of the 4-item scale by Tarafdar et al. (2007) in T2. The exact wording of the items together with their descriptive statistics is provided in Table A.6. The internal consistency of digital productivity was acceptable ($\alpha = 0.82$, $\omega = 0.82$). CFA results indicated superior model fit ($\chi^2 = 5.71$, df = 2; $\chi^2$/df = 2.86; CFI = 0.97; IFI = 0.98; TLI = 0.92; SRMR = 0.04).

A.1.1.7 Digital Work Performance

Digital work performance was measured using one item in T2: “How often have you reliably achieved desired work outcomes through the use of technology within the last month?”. We used a 5-point Likert scale type ranging from 1 (never) to 5 (always). Descriptive statistics are provided in Table A.6.
Table A.1: Descriptive Statistics of the Resistance to Change Scale

<table>
<thead>
<tr>
<th></th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Routine seeking</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 I generally consider changes to be a negative thing.</td>
<td>2.39</td>
<td>1.18</td>
</tr>
<tr>
<td>2 I’ll take a routine day over a day full of unexpected events any time.</td>
<td>3.53</td>
<td>1.05</td>
</tr>
<tr>
<td>3 I like to do the same old things rather than try new and different ones.</td>
<td>2.92</td>
<td>1.14</td>
</tr>
<tr>
<td>4 <em>Whenever my life forms a stable routine, I look for ways to change it.</em></td>
<td>3.01</td>
<td>1.22</td>
</tr>
<tr>
<td>5 I’d rather be bored than surprised.</td>
<td>2.91</td>
<td>1.18</td>
</tr>
<tr>
<td><strong>Emotional reaction</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 If I were to be informed that there’s going to be a significant change regarding the way things are done at work, I would probably feel stressed.</td>
<td>3.38</td>
<td>1.15</td>
</tr>
<tr>
<td>2 When I am informed of a change of plans, I tense up a bit.</td>
<td>3.19</td>
<td>1.19</td>
</tr>
<tr>
<td>3 When things don’t go according to plans, it stresses me out.</td>
<td>3.40</td>
<td>1.15</td>
</tr>
<tr>
<td>4 If my boss changed the criteria for evaluating employees, it would probably make me feel uncomfortable even if I thought I’d do just as well without having to do any extra work.</td>
<td>2.97</td>
<td>1.13</td>
</tr>
<tr>
<td><strong>Short-term focus</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Changing plans seems like a real hassle to me.</td>
<td>3.25</td>
<td>1.15</td>
</tr>
<tr>
<td>2 Often, I feel a bit uncomfortable even about changes that may potentially improve my life.</td>
<td>2.89</td>
<td>1.35</td>
</tr>
<tr>
<td>3 When someone pressures me to change something, I tend to resist it even if I think the change may ultimately benefit me.</td>
<td>2.86</td>
<td>1.23</td>
</tr>
<tr>
<td>4 I sometimes find myself avoiding changes that I know will be good for me.</td>
<td>2.84</td>
<td>1.21</td>
</tr>
<tr>
<td><strong>Cognitive rigidity</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 <em>I often change my mind.</em></td>
<td>3.18</td>
<td>1.13</td>
</tr>
<tr>
<td>2 Once I’ve come to a conclusion. I’m not likely to change my mind.</td>
<td>3.33</td>
<td>1.06</td>
</tr>
<tr>
<td>3 I don’t change my mind easily.</td>
<td>3.47</td>
<td>1.08</td>
</tr>
<tr>
<td>4 My views are very consistent over time.</td>
<td>3.84</td>
<td>0.90</td>
</tr>
</tbody>
</table>

*Note. N = 129; M = mean; SD = standard deviation; * = reversed item; italics = excluded items.*
### Table A.2: Descriptive Statistics of the Locus of Control Scale

<table>
<thead>
<tr>
<th>Item</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Internality</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Whether or not I get to be a leader depends mostly on my ability.</td>
<td>3.76</td>
<td>0.95</td>
</tr>
<tr>
<td>2 Whether or not I get into a car accident depends mostly on how good</td>
<td>3.12</td>
<td>1.17</td>
</tr>
<tr>
<td>a driver I am.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 When I make plans, I am certain to make them work.</td>
<td>4.05</td>
<td>0.78</td>
</tr>
<tr>
<td>4 How many friends I have depends on how nice a person I am.</td>
<td>3.43</td>
<td>1.10</td>
</tr>
<tr>
<td>5 I can pretty much determine what will happen in my life.</td>
<td>3.64</td>
<td>0.93</td>
</tr>
<tr>
<td>6 I am usually able to protect my personal interests.</td>
<td>4.16</td>
<td>0.63</td>
</tr>
<tr>
<td>7 When I get what I want, it is usually because I worked hard for it.</td>
<td>4.16</td>
<td>0.74</td>
</tr>
<tr>
<td>8 My life is determined by my own actions.</td>
<td>3.96</td>
<td>0.80</td>
</tr>
<tr>
<td><strong>External orientation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 To a great extent, my life is controlled by accidental happenings.</td>
<td>2.60</td>
<td>1.15</td>
</tr>
<tr>
<td>2 Often there is no chance of protecting my personal interests from bad luck happenings.</td>
<td>2.65</td>
<td>1.10</td>
</tr>
<tr>
<td>3 When I get what I want, it is usually because I am lucky.</td>
<td>2.58</td>
<td>1.14</td>
</tr>
<tr>
<td>4 I have often found that what is going to happen will happen.</td>
<td>3.22</td>
<td>1.08</td>
</tr>
<tr>
<td>5 Whether or not I get into a car accident is mostly a matter of luck.</td>
<td>2.71</td>
<td>1.15</td>
</tr>
<tr>
<td>6 It is not always wise for me to plan too far ahead because many things turn out to be a matter of good or bad fortune.</td>
<td>2.47</td>
<td>1.17</td>
</tr>
<tr>
<td>7 Whether or not I get to be leader depends on whether or not I am lucky enough to be in the right place at the right time.</td>
<td>2.68</td>
<td>1.12</td>
</tr>
<tr>
<td>8 Is is chiefly a matter of fate whether or not I have a few friends or many friends.</td>
<td>2.38</td>
<td>1.11</td>
</tr>
</tbody>
</table>

*Note. N = 129; M = mean; SD = standard deviation; italics = excluded items.*
### Table A.3: Descriptive Statistics of the Locus of Control Scale (continued)

<table>
<thead>
<tr>
<th>Item</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. I feel like what happens in my life is mostly determined by powerful people.</td>
<td>2.53</td>
<td>1.25</td>
</tr>
<tr>
<td>2. Although I might have good ability, I will not be given leadership responsibility without appealing to those in positions of power.</td>
<td>2.91</td>
<td>1.23</td>
</tr>
<tr>
<td>3. My life is chiefly controlled by powerful others.</td>
<td>2.45</td>
<td>1.18</td>
</tr>
<tr>
<td>4. People like myself have very little chance of protecting our personal interests when they conflict with those of strong pressure groups.</td>
<td>2.77</td>
<td>1.25</td>
</tr>
<tr>
<td>5. Getting what I want requires pleasing those people above me.</td>
<td>3.23</td>
<td>1.10</td>
</tr>
<tr>
<td>6. If important people were to decide they didn’t like me, I probably wouldn’t make many friends.</td>
<td>2.59</td>
<td>1.17</td>
</tr>
<tr>
<td>7. Whether or not I get into a car accident depends mostly on the other driver.</td>
<td>2.90</td>
<td>1.00</td>
</tr>
<tr>
<td>8. In order to have my plans work, I make sure that they fit in with the desires of people who have power over me.</td>
<td>2.95</td>
<td>1.12</td>
</tr>
</tbody>
</table>

*Note.* $N = 129; M = \text{mean}; SD = \text{standard deviation}.$

### Table A.4: Descriptive Statistics of the General Self-efficacy Scale

<table>
<thead>
<tr>
<th>Item</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. I will be able to achieve most of the goals that I have set for myself.</td>
<td>4.08</td>
<td>0.68</td>
</tr>
<tr>
<td>2. When facing difficult tasks, I am certain that I will accomplish them.</td>
<td>3.89</td>
<td>0.86</td>
</tr>
<tr>
<td>3. In general, I think that I can obtain outcomes that are important to me.</td>
<td>4.19</td>
<td>0.73</td>
</tr>
<tr>
<td>4. I believe I can succeed at most any endeavor to which I set my mind.</td>
<td>4.07</td>
<td>0.78</td>
</tr>
<tr>
<td>5. I will be able to successfully overcome many challenges.</td>
<td>4.09</td>
<td>0.67</td>
</tr>
<tr>
<td>6. I am confident that I can perform effectively on many different tasks.</td>
<td>4.19</td>
<td>0.73</td>
</tr>
<tr>
<td>7. Compared to other people, I can do most tasks very well.</td>
<td>4.05</td>
<td>0.75</td>
</tr>
<tr>
<td>8. Even when things are tough, I can perform quite well.</td>
<td>4.08</td>
<td>0.71</td>
</tr>
</tbody>
</table>

*Note.* $N = 129; M = \text{mean}; SD = \text{standard deviation}.$
Table A.5: Descriptive Statistics of the Computer Self-efficacy Scale

<table>
<thead>
<tr>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.91</td>
<td>0.85</td>
</tr>
<tr>
<td>3.34</td>
<td>0.89</td>
</tr>
<tr>
<td>3.86</td>
<td>0.88</td>
</tr>
<tr>
<td>3.94</td>
<td>0.92</td>
</tr>
<tr>
<td>4.16</td>
<td>0.89</td>
</tr>
<tr>
<td>4.20</td>
<td>0.77</td>
</tr>
<tr>
<td>4.26</td>
<td>0.79</td>
</tr>
<tr>
<td>3.88</td>
<td>0.83</td>
</tr>
<tr>
<td>4.34</td>
<td>0.70</td>
</tr>
<tr>
<td>4.39</td>
<td>0.73</td>
</tr>
</tbody>
</table>

Often in our jobs we are told about software packages that are available to make work easier. For the following questions, imagine that you were given a new software package for some aspect of your work. It doesn’t matter specifically what this software package does, only that it is intended to make your job easier and that you have never used it before. Please indicate how confident you would be to complete your job using the new digital technology under a variety of conditions:

1. if there was no one around to tell me what to do as I go.
2. if I had never used a package like this before.
3. if I had only the software manuals for reference.
4. if I had seen someone else using it before trying it myself.
5. if I could call someone for help if I got stuck.
6. if someone else had helped me get started.
7. if I had a lot of time to complete the job for which the software was provided.
8. if I had just the built-in help facility for assistance.
9. if someone showed me how to do it first.
10. if I had used similar packages before this one to do the same job.

Note. N = 129; M = mean; SD = standard deviation; italics = excluded items.
### Table A.6: Descriptive Statistics of the Performance Measures

<table>
<thead>
<tr>
<th>In-role performance</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Think about the last four work weeks and evaluate the extent to which you agree with</td>
<td></td>
<td></td>
</tr>
<tr>
<td>the statements. In the last four weeks I...</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 adequately completed assigned duties.</td>
<td>4.47</td>
<td>0.63</td>
</tr>
<tr>
<td>2 fulfilled responsibilities specified in my job description.</td>
<td>4.53</td>
<td>0.64</td>
</tr>
<tr>
<td>3 performed tasks that are expected of me.</td>
<td>4.53</td>
<td>0.59</td>
</tr>
<tr>
<td>4 met formal performance requirements of the job.</td>
<td>4.44</td>
<td>0.67</td>
</tr>
<tr>
<td>5 engaged in activities that will directly affect my performance evaluation.</td>
<td>4.12</td>
<td>0.96</td>
</tr>
<tr>
<td>6 <em>neglected aspects of the job I am obligated to perform.</em></td>
<td>4.14</td>
<td>1.15</td>
</tr>
<tr>
<td>7 <em>failed to perform essential duties.</em></td>
<td>4.24</td>
<td>1.12</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Digital productivity</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Technology helps to improve the quality of my work.</td>
<td>4.40</td>
<td>0.58</td>
</tr>
<tr>
<td>2 Technology helps to improve my productivity.</td>
<td>4.48</td>
<td>0.64</td>
</tr>
<tr>
<td>3 Technology helps me to accomplish more work than would otherwise be possible.</td>
<td>4.40</td>
<td>0.74</td>
</tr>
<tr>
<td>4 Technology helps me to perform my job better.</td>
<td>4.36</td>
<td>0.69</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Digital work performance</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 How often have you reliably achieved desired outcomes through use of technology</td>
<td>4.22</td>
<td>0.69</td>
</tr>
<tr>
<td>within the last month?</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note. N = 129; M = mean; SD = standard deviation; * = reversed item; italics = excluded items.*
Declaration of Authorship

I hereby declare that chapter 2 “Digital Fluency — A Key Employee Resource to Perform in the Digital Age?” is based on joint work with Prof. Dr. Florian Kunze, holder of the chair for Organisational Studies at the Department for Politics and Public Administration at the University of Konstanz. As lead author of this joint paper, I developed the research question, wrote the manuscript and conducted the empirical analysis. Over multiple rounds of revisions, Florian Kunze supported me in framing and re-writing parts of the paper.

In sum, I declare that I am the sole author of chapter 1, chapter 3, chapter 4, and chapter 5 as well as the supplemental materials, and the lead author of chapter 2.
References


REFERENCES


