Developers Task Satisfaction and Performance during the COVID-19 Pandemic

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Abstract Following the onset of the COVID-19 pandemic and subsequent
lockdowns, software engineers’ daily life was disrupted and they were abruptly
forced into working remotely from home. Across one exploratory and one
confirmatory study (N = 482), we tested whether a typical working day is
different to pre-pandemic times and whether specific tasks are associated with
task-specific satisfaction and productivity. To explore the subject domain,
we first run a two-wave longitudinal study, where we found that the time
software engineers spent doing specific tasks (e.g., coding, bugfixing, helping
others) from home was similar to pre-pandemic times. Also, the amount
time developers spent on each task was unrelated to their general well-
being, perceived productivity, and other variables such as basic needs. In
our confirmatory study, we found that task satisfaction and productivity
are predicted by task-specific variables (e.g., how much autonomy software
engineers had during coding) but not by task-independent variables such as
general resilience or a good work-life balance. Additionally, we found that
satisfaction and autonomy were significantly higher when software engineers
were helping others and lower when they were bugfixing. Also, contrary to
anecdotal evidence, software engineers’ satisfaction and productivity during

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meetings is not lower compared to other tasks. Finally, we discuss implications for software engineers, management, and researchers.

**Keywords** Pandemic · COVID-19 · Productivity · Well-being · Longitudinal Study · Remote Work · Working From Home

1 Introduction

The SARS-CoV-2 (or COVID-19) pandemic abruptly disrupted software developers working routines in an unprecedented way. Many software developers were asked to switch their typical office-based working habits to a new working from home (WFH) setting on short notice. This has had a considerable negative impact on developers' well-being and productivity [65]. Nonetheless, longitudinal research has also shown that software engineers can successfully adapt over time, suggesting that their well-being and productivity bounce back to the pre-pandemic level [29,30,2,69]. This is encouraging, as 89% of professionals would like to work from home at least one day per month after the pandemic [34]. For this reason, major IT companies (e.g., Twitter, Microsoft, AirBnB, Uber, Facebook) informed their employees that they could work from home indefinitely (e.g., Twitter) or extended the remote work policies providing specific support (e.g., AirBnB) [35]. Thus, research conducted during the pandemic will very likely be valuable once restrictions have been lifted again, too.

Remote work (or telework), *per se* is not a new topic in software engineering. With the rise of the internet in the late 90s, scholars started asking themselves about the challenges and opportunities of working from home [63]. Researchers investigated specific software development practices, such as processes [34,20] or communication [40] to better tailor working from home practices to business needs. Also, collaboration and characteristics of remote and asynchronous projects have been extensively studied by the Global Software Engineering community [39,75]. Such studies typically focus on the interaction of software development teams co-located in different geographical areas. However, the focus has been on software development teams working together on distributed projects.

There is a growing agreement in the practitioners’ community that working from home is different from working remotely on distributed projects [1]. While working from home is understood as working from the main address of residence, such as an apartment or house, working remotely is carried out typically in coworking spaces or in different settings where one lives. So far, the research on WFH practices has been quite limited. One reason is that managers are pretty skeptical about remote working due to worries concerning employees’ reduced focus, productivity, company culture, or team cohesiveness [10], resulting in a relatively small population suitable for WFH studies. Nevertheless, the pandemic made many of us realize that some fears are often unfounded (such as decreasing productivity) and that we have to face such challenges until a sufficient number of people have been vaccinated, a process that might take
several years. Hence, anecdotal evidence driving top managerial decisions due to the lack of specific research [55] should be supplemented with scholarly evidence.

In this paper, we explore how software engineers’ activities changed during the pandemic using the activity taxonomy of Meyer et al. [56], whether specific activities contribute to software engineers’ well-being and productivity, and what factors contribute to their satisfaction and productivity while working on a particular task. For example, there is countless anecdotal evidence that meetings are a waste of time [41,79]. Does this imply that software developers’ perceived productivity is lower when they have more meetings, and more meetings are also associated with lower well-being and boredom?

Further, we test whether professionals’ needs influence the time they spend on various activities. In their seminal paper, Ryan and Deci [71] describe three innate psychological needs that motivate us and guide our behavior: the need for autonomy, competence, and relatedness. The need for autonomy measures whether people feel independent; competence, whether people feel that they can complete various (challenging) tasks; and relatedness whether people feel appreciated by others important to them. Self-determination theory has frequently been used in the work context to predict job satisfaction and performance [31]. Indeed, research established that all self-determination theory-related needs (need for autonomy, need for relatedness, and need for competence) positively correlate with job satisfaction, and productivity [8].

We also take social relations into account: People who feel that communication with their colleagues and line managers might be more inclined to spend time in meetings, helping, and other social activities. Most previous research which investigated predictors of well-being and stress in occupational settings [6,23,53] has not measured the specific activities that might have contributed to higher stress and lower levels of well-being. However, the type of activity someone is doing might contribute to higher stress levels beyond other factors identified by previous research, such as support by coworkers and supervisors [12]. If we were to determine what specific activities are associated with higher or lower levels of stress or well-being, this would provide valuable information for future research investigating predictors of stress.

Thus, we formulate the following five main research questions:

**Research Question 1:** Has the distribution of daily working activities of software engineers changed while WFH during the pandemic as compared to pre-pandemic daily working activities?

**Research Question 2:** Is the distribution of daily working activities related to well-being, productivity, and other variables?

**Research Question 3:** Do the needs for autonomy, competence, and relatedness predict software engineers’ task-specific satisfaction and productivity?

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1 We are using the terms “activity” and “tasks” interchangeable.
Research Question 4: Are the associations between task satisfaction and productivity moderated by resilience and company support?

Research Question 5: Do software engineers’ work activities while WFH during the pandemic affect their task-specific well-being, productivity, and psychological needs?

This paper is divided into an exploratory part in which we investigate RQ1 and RQ2 and a confirmatory part in which we test RQ3, RQ4, and RQ5. In the exploratory part, we first collected information regarding developers’ activities and self-reported well-being and productivity measures to assess changes along with the lockdown over two weeks. We compared wave 1 with wave 2 to assess our test-retest reliability and stability of the data during the pandemic. In particular, we found that the time software engineers spent doing specific activities from home was overall comparable when working in the office pre-pandemic. Nevertheless, we also reported some significant mean differences, such as less time dedicated to meetings and breaks and more specification and documentation. Interestingly, the number of time people spent on each activity was unrelated to their general well-being, perceived productivity, and other variables. In hindsight, this is not surprising because many factors affect our well-being and productivity. For example, well-being is impacted by many factors such as quality of our relationships, personality, or situational factors (e.g., weather) [14,21,69], which makes it unlikely that spending an hour more or less on a specific task will impact well-being. However, what we believe is more likely to impact well-being and productivity, are task-specific features, which is one of the primary motivations of this confirmatory study. That is, what factors predict task-specific well-being and productivity?

In the confirmatory study, we measured task-specific well-being, productivity, as well as the task-specific need for autonomy, competence, and relatedness (e.g., how productive professionals felt during the task they spend the most time on a day). Additionally, we explored whether task-unrelated variables such as resilience or work-life balance would moderate the link between task-specific needs and task-specific well-being and productivity (for a more detailed rationale, see below). Together, through our exploratory-confirmatory design, we showed which tasks make professionals more satisfied. We also characterized when doing which tasks people felt more satisfied, productive, autonomous, competent, and connected.

In the remainder of this paper, we describe the related work in Section 2 followed by a description of our research design in Section 3. The analysis and related results of our analysis are described in Section 4. Implications and recommendations for software engineers and organizations are then outlined in Section 5. Finally, we conclude this study by outlining future research directions in Section 6.
2 Related Work

Several large software companies, such as Stack Overflow or Red Hat, have embraced working from home by designing *ad hoc* schemes already before the start of the 2020-Corona pandemic [52,66]. Organizations do so to increase their employees’ job satisfaction and productivity while simultaneously reducing their operating expenses, such as office rent [27,62]. However, thus far, the software engineering literature did not primarily investigate working from home challenges, with a few exceptions. To find previous work, we looked into peer-reviewed publications in Scopus. We identified eleven relevant papers. Considering the vast but recent impact of COVID-19, we also selected non-peer-reviewed pre-prints on arXiv (one in total). Table 1 summarizes prior studies of remote working issues related to software engineers.

Our overview highlights how the subject matter arose with more extensive use of the internet (the late 90s), but it was simultaneously a relatively neglected topic until very recently. Indeed, most papers on WFH have been published in 2019 onward and are dealing with the enforced WFH because of the COVID-19 pandemic. From a methodological perspective, most studies have been field studies involving a single company (e.g., Fujitsu, Baidu, Microsoft) [2,29,40,58,11]. Such real-world investigations aimed to understand the research phenomena by generating research hypotheses. Three studies were conducted in a neutral setting on the opposite spectrum by asking participants a quantifiable judgment and analyzing such data through statistical techniques. These four sample studies generalize their result on the entire software engineering population [65,69,50,15].

Content wise, half of the papers are concerned with specific topics related to working from home, such as security [63,43], process [34], work productivity [40,47], and inclusion [28]. The other half mostly investigated well-being and productivity while working from home during the pandemic [29,65,69,11,50] and productivity-related to projects’ characteristics [2,15].

It is evident from the few related work that remote working in software engineering is an under-researched topic. Possibly, one reason might be that businesses in the IT sector, allowing software professionals to work from home in a structured way, are relatively few [67]. Most importantly, to this work, to the best of our knowledge, no one so far analyzed specific working activities while working from home and how this influences both the perceived productivity and well-being of software engineers, as well as factors that influence task-specific productivity and satisfaction.

3 Research Design

To answer our research questions in a reliable and meaningful way, we employed a post-positivist epistemological stance. We were guided by the relevant ACM SIGSOFT Empirical Standards for longitudinal and sample studies [64]. First, we applied an exploratory longitudinal design already described in Russo
| Study                        | Method                        | Findings                                                                 |
|-----------------------------|-------------------------------|--------------------------------------------------------------------------|
| Cucolas & Russo (2021)      | Multi-Methods study. Qualitative interviews and sample study of Scrum developers. After a theoretical model was induced from qualitative data, a sample study of 200 software engineers validated it with PLS-SEM. | Home-working environment is the most important variable for project success, and to improve WFH conditions, organizations should strengthen the need for autonomy, competence, and relatedness of developers. Communication and interaction with colleagues is a relevant predictor of developers’ satisfaction and team productivity. |
| Miller et al. (2021)       | Field study. Mixed-methods investigation of Microsoft developers. Two surveys collected information about working from home and team-related issues. Data were analyzed using different quantitative and qualitative techniques. | The largest identified challenges were meetings, overwork, and physical and mental health. On the other hand, participants appreciated to have more family time and work flexibility. The pandemic affected differently men and women. Organizations should accommodate women first when schedule meetings. Organize uninterrupted work sessions and support childcare are also recommended. |
| Butler & Jaffe (2021)       | Field study. Diary study of 435 Microsoft developers over 10 weeks during the lockdown. Data were analyzed using different quantitative and qualitative techniques. | Quality of family life and time improved, although WFH might have led to a lack of focus, poor work-life boundaries, communications, and sync issues, developers adapt over time. |
| Machado et al. (2021)       | Sample study. Mixed-methods investigation of 233 Brazilian software professionals. Data were analyzed using different quantitative and qualitative techniques. | Confirmation of a theoretical model. Professionals’ well-being and productivity are suffering; well-being and productivity are strongly related to each other; women are disproportionately affected by this peculiar remote working setting. |
| Ford et al. (2020)          | Field study. Mixed-methods investigation of 3,634 Microsoft developers. Two surveys collected qualitative and quantitative insights about WFH conditions during the COVID-19 lockdown. | Well-being and productivity are related, professionals adapt to the condition over time, improving their well-being and productivity, introverts are significantly able to causally explain the variance in well-being and productivity. |
| Ralph et al. (2020)         | Sample study. Large-scale cross-sectional study of 2,225 software developers globally working from home during the COVID-19 lockdown, surveying five variables. Data were analyzed using covariance-based structural equation modeling. | Working from home enables the empowerment and identity disclosure of software professionals from marginalized communities. |
| Russo et al. (2020)         | Sample study. Longitudinal study involving 192 software engineers living in countries with comparable COVID-19 lockdown measures, surveying 51 variables. Data were analyzed using correlations, multiple linear regressions, and covariance-based structural equation modeling to assess predictive causal relations. | Development of a mobile execution environment to support a secure and portable working from home setting. |
| Ford et al. (2019)          | Field study. Qualitative study interviewing three transgender software engineers to explore the interplay of gender identity and remote work. | Development of the Software Process Improvement approach for Teleworking Environment (SPITE) model. Identification of 25 base practices to improve software processes when working from home. |
| James & Griffiths (2014)    | Experimental simulation. Within an existing project, relevant working from home problems have been identified and addressed by developing and validating a specific solution. | An effective use of E-mails by remote workers leads to better work distribution and work productivity. |
| Guo (2001)                  | Field study. Report of two qualitative surveys regarding software process improvement related to the distinctive characteristics of teleworking. | This is the first paper that considers “homeworking” as a distinct working setting. It discusses the main security concerns and makes recommendations for organizations. |
| Higa et al. (2000)          | Field study. Mixed-methods study at Fujitsu with 44 software engineers to investigate how the use of E-mail influences telework. To test the hypotheses, three hierarchical regression models were used. | |
| Pounder (1998)              | Formal theory. Essay about security problems linked to telework. | |
et al. [58]. Subsequently, to overcome the methodological limitations of the exploratory study while gaining further insights into the associations of activities with task-specific satisfaction, productivity, and basic needs, we employed a cross-sectional design. We designed the exploratory study to answer RQ1 and RQ2, whereas the confirmatory research was designed to answer RQ3 to RQ5.

Our first concern was to recruit software professionals for our exploratory study carefully. We asked them to complete the same survey on two occasions. Unique randomized IDs were assigned to participants to preserve their anonymity and track their participation across both waves. To address concerns about replicability and increase the reliability of our findings, we asked the same participants to complete all measures twice, two weeks apart. Specifically, to test whether the distribution of daily working activities has changed. At the same time, WFH during the pandemic (i.e., investigate RQ1), we asked participants to report how much time they spend on 15 activities and compared the responses with a pre-pandemic sample [56]. To test RQ2 – is the time spent on different activities correlated with well-being, productivity, and other variables – we correlated the time spent on each activity with professionals’ general well-being, productivity, and other variables.

In a subsequent confirmatory study, we asked participants about their well-being, productivity, autonomy, competence, and relatedness to their co-workers while completing specific tasks (e.g., ”how stressed were you while coding?”). Specifically, to test RQ3 – whether the needs for autonomy, competence, and relatedness predict software engineers’ task-specific satisfaction and productivity – we asked how satisfied, productive, autonomous, competent, and related with their co-workers participants felt during working on a specific activity (e.g., coding). Our design allowed us to test RQ3 across all tasks but also separately for each task.

Additionally, to investigate RQ4 – whether the associations between autonomy, competence, and relatedness are moderated by resilience and company support – we also included a range of conceptually related variables that measure facets of company support: caring leadership, work-life balance, empowerment, job enablement, soft company support, hard company support, and recognition. We expect that software engineers who are more resilient and receive higher company support are less likely to be affected by, for example, reduced autonomy for a specific task. For instance, resilience or recognition might buffer against reduced autonomy because resilient people are more likely to ‘bounce back after stressful events such as being less able to make autonomous decisions [76,85]. In other words, we expect the effect of the three needs on task satisfaction and productivity to be reduced if resilience and company support is high.

Finally, to test RQ5 – does the task impact task-specific satisfaction, productivity, and psychological needs – we tested during which task professionals felt relatively more or less satisfied, productive, and so on.
3.1 Participants

For the exploratory study, a power analysis using G*Power version 3.1 revealed that to detect a small-to-medium effect size of $r = .20$, using a power of .80 (for a two-sided test), a sample size of at least 190 participants is required. Participants were selected from a broader set of 500 software engineers who were carefully selected through a multistage process in a previous study by Russo & Stol [70]. We only selected professionals working from home during the pandemic and live in countries with comparable lockdown measures from this pool. Finally, we obtained a sample of 192 software engineers who completed the first survey ($M_{\text{age}} = 36.65$ years, $SD = 10.77$, range = 19–63; 154 men, 38 women). Of those, 184 participated in the second wave two weeks later. We provide demographic information on participants’ gender, age, and location in Table 2. We collected our data between 20 and 26 April 2020 (wave 1) and between 4 and 10 May 2020 (wave 2).

To identify the participants for the confirmatory study, we also first run a power analysis, which revealed that a sample size of 77 is sufficient to detect a medium effect size with three predictors (i.e., need for autonomy, competence, and relatedness) with a power of .80. However, to keep the length of the survey to a manageable amount, participants only selected three tasks they performed during the day. They completed a series of questions that expressly referred to each of the three tasks. We, therefore, aimed to recruit around 300 participants, to get for multiple tasks the required sample size of 77. To ensure that the participants were effectively software engineers, we run a pilot study to screen our informants with the questions developed by Danilova et al. [17]. Of the 300 selected participants, 10 participants failed at least one test item and/or completed the survey in less than 4 minutes and were excluded. Of the remaining 290 participants, 49 participants lived alone, 241 with other people. 62 had an income in 2020 before taxes of $< 20,000$, 93 of $20,000-40,000$, 70 of $40,000-60,000$, 36 of $60,000-80,000$, 18 of $80,000-100,000$, and 21 participants of $> 100,000$ (all in US$). The vast majority of participants, 210, worked in ‘Software & IT,’ 20 in ‘Education & Research,’ and 11 in ‘Finance, banking & insurance.’

To ensure high data quality [60], we recruited participants from the academic data collection platform Prolific Academic and compensated participants above the US minimum wage. The survey was run using Qualtrics.

3.2 Measurements for the exploratory longitudinal study

For the exploratory study, we derived the variables from a related project. For a complete presentation of the used instruments, we directly refer to Russo et

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With $r$, we mean Pearson’s $r$, which is a measurement of linear association between two variables; its values range between -1 (strongly negative associated) and +1 (strongly positively associated). Values around 0 suggest that there is no meaningful association between two variables.
Table 2: Demographic information of both samples

| Sample size          | N Exploratory study | N Confirmatory study |
|----------------------|---------------------|----------------------|
| United Kingdom       | 61 (31.8%)          | 36 (12.4%)           |
| United States        | 49 (25.5%)          | 22 (7.6%)            |
| Portugal             | 19 (9.9%)           | 54 (18.6%)           |
| Poland               | 10 (5.2%)           | 63 (21.7%)           |
| Italy                | 7 (3.6%)            | 13 (4.5%)            |
| Ireland              | 5 (2.6%)            | 3 (1.0%)             |
| Other                | 41 (21.4%)          | 99 (34.1%)           |
| Women                | 38 (19.8%)          | 48 (16.6%)           |
| Mean age ($SD$, range) | 36.7 (10.7, 19-63)  | 25.85 (6.44, 18-60)  |

al. [69] and the Supplementary Materials. The longitudinal design also allowed us to compute test-retest reliabilities, \( r_{tt} \) (i.e., the stability of responses across two or more time-points), by correlating responses given by participants at time 1 with those at time 2 (we are using \( \text{time} \) and \( \text{wave} \) interchangeably), which provides additional information about a scale’s reliability to the commonly used Cronbach’s alpha [54]. Coefficients close to 0 are undesirable since they indicate a low association between the two-time points, suggesting, among others, poor data quality.

**Activities.** We measured the same 15 activities that were measured by Meyer et al. [56]. We did this because we believe they covered most activities and to have a pre-pandemic comparison group. We asked participants, “During the past week, how much time did you spend on each task percentage-wise (%)?” This was followed by the 15 activities (e.g., ‘Coding,’ ‘Email,’ ‘Bugfixing’), rated on a slider-scale ranging from 0% to 100%. For the activities which might have been more ambiguous, a brief explanation was added in brackets such as ‘Helping (helping, managing or mentoring people),’ ‘Networking (maintaining relationships).’

**Well-being.** We used the Satisfaction with Life Scale [22]. Our Cronbach’s alpha \( \alpha \) values to measure internal consistency for both waves were the following \( \alpha_{time1} = .90, \alpha_{time2} = .90 \) (\( r_{tt} = .72, p < .001 \)).

**Productivity.** Measuring productivity in software engineering is a highly debated issue. Some scholars, for example, suggest making the measurement more objective by using function points [83]. Ko has criticized this viewpoint as being detrimental in the long run [46]. On the other hand, other researchers propose a self-reflection measure with developers’ self-reporting their daily productivity [57]. In this work, we adopted a similar approach. We did not

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3 Cronbach’s alpha is a measure of scale reliability. For exploratory research, using new measurement scales, values above .60 are desirable while for confirmatory research the threshold is above .70 (and below .95) [66].
use a standard measure (e.g., such as Ralph et al. [65] did). Productivity was operationalized as a function of time spent working and efficiency per hour, compared to a typical week. The reason for this choice is that we wanted to investigate the variance in productivity while working remotely as compared to being in the office ($r_{it} = .50, p < .001$).

**Stress.** We used the Perceived Stress Scale [13]; $\alpha_1 = .80$, $\alpha_2 = .77$ ($r_{it} = .73, p < .001$).

**Boredom.** We used the Boredom Proneness Scale [25, 78]; $\alpha_1 = .87$, $\alpha_2 = .87$ ($r_{it} = .69, p < .001$).

**Autonomy, competence, and relatedness.** To measure the three needs of the self-determination theory [71], we used the psychological needs scale [73]. Need for autonomy’s Cronbach’s alpha level were: $\alpha_1 = .72$, $\alpha_2 = .76$ ($r_{it} = .76, p < .001$); for Competence: $\alpha_1 = .77$, $\alpha_2 = .65$ ($r_{it} = .76, p < .001$); and for Relatedness: $\alpha_1 = .79$, $\alpha_2 = .78$ ($r_{it} = .71, p < .001$).

**Quality and quantity of communication with colleagues and line managers.** We used a self-developed three items instrument ($\alpha_1 = .88$, $\alpha_2 = .92$; $r_{it} = .67, p < .001$).

**Daily Routines.** We developed a five items scale ($\alpha_1 = .75$, $\alpha_2 = .78$; $r_{it} = .73, p < .001$).

**Distractions at home.** We developed a two items scale ($\alpha_1 = .64$, $\alpha_2 = .63$; $r_{it} = .63, p < .001$).

3.3 Measurements for the confirmatory cross-sectional study

3.3.1 Measurement of task-specific variables

After providing informed consent, participants were instructed "Which of the following tasks have you spent most time with yesterday? For example, when you spent most of your time in two meetings, pick the meeting that went longer. Select three tasks." Participants selected three of the tasks we used in Study 1, except breaks, interruptions, and various, which were excluded, leaving 12 tasks: Coding (n = 192), buxfixing (111), testing (96), specification (22), reviewing (91), documenting (40), meetings (87), emails (51), helping (33), networking (11), learning (93), and administration (14). Participants then completed 17 items for each task, 8 measuring our two dependent variables, well-being and productivity, and 9 measuring our three independent variables, need for autonomy, competence, and relatedness. The two dependent variables were measured with 8 items.

**Well-being** was measured with six items (e.g., “After completing the task, I felt tired” and “I felt exhausted after the task”; both example items were recorded) and were answered on a scale ranging from 1 (Not at all) to 7 (Very). A principal component analysis revealed that the 6 items were loading on one component, with good internal consistency ($\alpha = .80$).

**Productivity** was measured with two items: “How productive have you been during this task?”, which was answered on a scale ranging from 1 (Not at
all) to 7 (Very), and “What percentage of your goals have you reached during
<task>,” which was answered on a 0-100 scale. Both items were standardized
before averaged ($\alpha = .50$).

To measure the three independent variables, we adapted three items for
each of the three needs of the self-determination theory [71] from the balanced
measure of psychological needs scale [72]. All items were answered on a 7-point
response scale varying from 1 (Not at all) to 7 (Fully) with an 8th option, ‘Not
applicable.’

**Need for autonomy** was measured with “I was really doing what interests
me,” “I was free to do things my own way,” and “I had a lot of pressures I
could do without when working on the task” (recoded). However, as the last
item was uncorrelated with the other two, $r = -.00$ and -.14, we only combined
the first two items ($\alpha = .46$) into an Autonomy factor and included the last
item as a single-item predictor.$^4$

**Need for relatedness** was measured with “I felt close and connected with
people working on the same task as me,” “I felt appreciated by one or more
people working on the same task as me,” and “I had disagreements or conflicts
with people working on the same task as me” (recoded). However, as the last
item was uncorrelated with the other two, $r = .09, .06$, we only combined the
first two items ($\alpha = .73$) into a relatedness factor and included the last item
as a single-item predictor.$^5$

**Need for competence** was measured with “I was successfully completing
the task,” “I did well even at the hard things,” and “I struggled to complete
the task” (recoded; $\alpha = .64$). Thus, instead of the three predictors, we now
have five, two of which are single item predictors. While single-item scales are
sometimes considered as problematic because of possible low reliability, they
are often used in research and – assuming there is evidence that participants
paid attention as evidenced through good internal consistencies of other scales
– can produce meaningful findings [32,87]. Indeed, the results of the measures
with the two single items are in line with expectations (see below).

### 3.3.2 Measurement of task-independent variables

Additionally, we also included variables that were suggested to be related to
our dependent variables from the exploratory investigation.

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$^4$ While the three items usually load on the same factor when measured in a non-specific
way [72] – also among software developers [69] – in the context of our study people still
can feel pressured to do a task while being able to do things their own way. This apparent
paradox is likely familiar to many researchers: They are often free to pick their own research
projects but might then feel pressured to complete them because of pressure from their
colleagues, from editors, or to advance in their career – especially if they have chosen to work
on too many projects. Also, given that we have adapted the established balanced measure of
psychological needs scale [72] and that the internal consistencies for the task-independent
variables are good (mostly $.75 \leq \alpha \leq .90$), we believe that the issue at hand is the adaptation
that unexpectedly did not work rather than the data quality.

$^5$ Some participants might have construed ‘disagreements or conflicts in the context of
specific tasks as ‘mild,’ which can happen among colleagues one is usually getting along well
or even has befriended [42].
**Resilience** was measured with the 6-item Brief Resilience Scale [76]. Participants indicate how much they agreed with statements such as “I tend to bounce back quickly after hard times” and “It is hard for me to snap back when something bad happens” (recoded). Responses were given on a 5-point scale ranging from 1 (Strongly disagree) to 5 (Strongly agree; $\alpha = .73$).

**Caring leadership** was measured with the 7-item Caring Leadership Scale [49]. Example items include “My manager develops an atmosphere of caring and trust” and “I feel free to discuss work problems with my manager without fear of having it used against me later.” Responses were given on a 5-point scale ranging from 1 (Strongly disagree) to 5 (Strongly agree; $\alpha = .85$).

**Work-life balance** was measured with a 5-item scale. Example items include ”My workload is manageable” and “I have the flexibility I need in my work schedule to meet both work and personal needs.” Responses were given on a 5-point scale ranging from 1 (Strongly disagree) to 5 (Strongly agree; $\alpha = .84$).

**Empowerment** was measured with a 7-item scale. Example items include “I am given the opportunity to be involved in decisions that affect me” and “Employees are encouraged to participate in decisions that affect their work.” Responses were given on a 5-point scale ranging from 1 (Strongly disagree) to 5 (Strongly agree; $\alpha = .83$).

**Job Enablement** was measured with a 7-item scale. Example items include “My job is challenging and interesting” and “My work-from-home workspace allows me to be productive.” Responses were given on a 5-point scale ranging from 1 (Strongly disagree) to 5 (Strongly agree; $\alpha = .77$).

**Soft company support** was measured with 3-items, including “My company is providing me with the necessary software tools to work from home” and “My company is providing me with the necessary flexibility so that I can work from home properly.” Responses were given on a 5-point scale ranging from 1 (Strongly disagree) to 5 (Strongly agree; $\alpha = .64$).

**Hard company support** was measured with 3-items, including “My company is supportive in providing me the necessary work from home setting (e.g., chair, screen, mouse).” and “From the start of the lockdown, my company is taking care also of things it didn’t do before (e.g., internet bill, electricity bill).” Responses were given on a 5-point scale ranging from 1 (Strongly disagree) to 5 (Strongly agree; $\alpha = .76$).

**Recognition** was measured with a 7-item scale. Example items include “I receive meaningful recognition when I do a good job” and “My manager values my contribution.” Responses were given on a 5-point scale ranging from 1 (Strongly disagree) to 5 (Strongly agree; $\alpha = .89$).

**4 Analysis & Results**

The following section will address our research questions and answer them based on the performed analyses.
3.1% 3.1% 3.6% 4.1% 4.6% 4.6% 5.2% 5.3% 5.5% 5.5% 7.9% 8.3% 10.1% 10.9% 18.3%

Fig. 1 Distribution software engineering work activities during the two waves in our study, and a typical workday of software engineers as reported by Meyer et al. [56].

4.1 RQ1: Has the distribution of daily working activities of software engineers changed while WFH during the pandemic as compared to pre-pandemic daily working activities?

Answering RQ1, we first compared the time participants reported to have spent on each of the 15 activities with those reported by Meyer et al. [56]. The results are displayed in Figure 1, as well as Tables 3 and 4. To test whether participants in our sample reported spending more or less of their time on certain activities than the software developers surveyed by Meyer et al. [56], we performed a series of one-sample $t$-tests. For example, we compared the percentages of participants in our sample at time 1 spend coding was significantly different from 15%, which is the percentage reported by Meyer et al. (see Table 3, second column). We performed 15 (activities) × 2 (time points) = 30 $t$-tests (two-tailed, since we did not have directed hypotheses).

Because of the large number of comparisons, we adjusted the $\alpha$-threshold from .05 to .003 to reduce the risk of false-positive results. This means that we considered only $p$-values of <.003 as statistically significant. This is a standard procedure for studies that involve many variables to ensure reliable results, e.g., [37]. Note that changing the $\alpha$-threshold impacts the test statistic (e.g., $t$-value), as the test statistic and $p$-value are perfectly associated with any given sample size [38]. For example, for an $\alpha$-threshold of .003 and a sample size of 192 (time 1) or 184 (time 2), the critical $t$-values are 3.006 and 3.008. In other words, only if the $t$-value obtained from a $t$-test is larger than 3.006 (or 3.008), the $p$-value would be < .003, and we would consider the test result to be statistically significant. Note that a Bonferroni correction would have resulted in an adjusted alpha-level of .05/30 ≈ .0017, which is overly conservative and does not consider that some variables are correlated (e.g., between time 1 and 2). Thus, the adjusted significance threshold of .003 seemed appropriate to us, neither overly conservative nor liberal.
Software engineers in our sample reported on average to have spent less time bugfixing, in meetings, getting interrupted (only at time 2), helping (only at time 2), and taking breaks; but more time on testing, specification, writing documentation, networking (only at time 1), learning, and administrative tasks compared to the participants surveyed by Meyer et al. (Table 3). However, the differences between what our participants and those of Meyer et al. reported differed by only a few percent (see Figure 1). This visual inspection of the data is supported by correlation analysis. The 15 activities expressing percentages reported by Meyer et al. correlated with $r(13) = .84, p < .0001$ at time 1 and with $r(13) = .83, p = .0001$ at time 2. To obtain those correlations, we correlated the mean percentages reported in columns 2-4 of Table 3 with each other. That is, we tested whether the average percentages spent on each activity reported by the participants in the Meyer et al. sample would align with those reported by the participants in our sample at waves 1 and 2. This suggests that while there are some deviations, the overall order of tasks remains stable. It further supports the quality of our data. If our participants had responded carelessly or even randomly, those two correlation coefficients would be around 0.

In the next step, we explored whether participants’ activities changed over time during the lockdown. To do this, we performed a series of paired $t$-tests (Table 4). The only statistically significant differences were observed for networking and taking breaks. At time 2, participants spent less time networking and taking breaks compared to time 1. Overall, the relative order of the activities remained very stable across time on the group level (i.e., when correlating the group averages for the activities of time 1 and 2), $r(13) = .99, p < .0001$.

4.2 RQ2: Is the distribution of daily working activities related to well-being, productivity, and other variables?

To test RQ2, we correlated the time participants spent on each activity with the selected variables. This was possible because the activities were mostly uncorrelated in both time points on an individual level. We report Pearson’s correlation coefficients ($r$) in our tables since most of the data were normally distributed. However, for the sake of completeness, we also ran a non-parametric Spearman’s rank correlations test (reported in the Supplementary Material), which provided us with very similar results, suggesting the robustness of our results. In total, we computed at both time points 13 (well-being related variables and productivity) × 15 (activities) = 195 correlations. Given a large number of comparisons, we changed our significance threshold from $\alpha = .05$ to .0005. Again, a Bonferroni correction would have resulted in an adjusted alpha level of .00017, which is overly conservative and does not consider that some variables are correlated (e.g., distractions and stress). Thus, the adjusted significance threshold of .0005 seemed appropriate to us, neither overly conservative nor liberal. This new threshold implies that only correlation

7 For the correlations, the Degrees of Freedom are $N - 2 = 13$ with $N = 15$ activities.
Table 3 Comparisons of both waves with time spend on activities as reported by Meyer et al. [56]

| Activity       | Meyer et al. | M1 | M2 | t-value 1 | t-value 2 | p1  | p2  |
|----------------|--------------|----|----|-----------|-----------|-----|-----|
| Coding         | 17%          | 18.11% | 19.85% | 0.901 | 1.89 | 0.369 | 0.060 |
| Bugfixing      | 14%          | 10.27% | 10.85% | −5.309 | −3.546 | <0.001 | <0.001 |
| Meetings       | 15%          | 8.45% | 9.74% | −9.951 | −6.628 | <0.001 | <0.001 |
| Testing        | 8%           | 10.96% | 11.36% | 3.413 | 3.321 | <0.001 | 0.001 |
| Email          | 10%          | 7.93% | 8.59% | −3.686 | −1.584 | <0.001 | 0.115 |
| Breaks         | 8%           | 5.21% | 3.40% | −7.391 | −14.297 | <0.001 | <0.001 |
| Code review    | 5%           | 5.44% | 5.01% | 0.878 | 0.019 | 0.381 | 0.985 |
| Specification  | 3%           | 5.40% | 5.76% | 4.653 | 4.048 | <0.001 | <0.001 |
| Learning       | 5%           | 5.30% | 6.07% | 4.242 | 3.377 | <0.001 | 0.001 |
| Helping        | 5%           | 4.25% | 3.60% | −2.126 | −3.964 | 0.035 | 0.003 |
| Administration | 2%           | 4.70% | 5.15% | 4.575 | 4.279 | <0.001 | <0.001 |
| Interruptions  | 4%           | 3.58% | 2.42% | −1.188 | −5.388 | 0.236 | <0.001 |
| Documentation  | 1%           | 4.69% | 3.77% | 5.178 | 5.073 | <0.001 | <0.001 |
| Various        | 3%           | 3.17% | 2.84% | 0.592 | −0.346 | 0.554 | 0.729 |
| Networking     | 2%           | 3.10% | 1.60% | 3.040 | −1.485 | 0.003 | 0.139 |

Note. Activity percentages as per ‘typical workday’ following Meyer et al. [56]. M1: mean at time 1 (see also Table 4). t-value 1: t-value of one-sample t-test from time 1 vs value reported by Meyer et al., p1: p-value of one-sample t-test from time 1.

Table 4 Comparisons of activities between time 1 and time 2

| Activity     | Time 1 M | SD    | Time 2 M | SD    | t     | p     | Cohen’s d | Higher | Smaller | Equal |
|--------------|----------|-------|----------|-------|-------|-------|-----------|--------|---------|-------|
| Coding       | 18.11%   | 16.97% | 20.44%   | 19.85% | −1.502 | 0.135 | −0.108    | 94     | 74      | 15    |
| Bugfixing    | 10.27%   | 9.72%  | 10.85%   | 12.03% | −0.422 | 0.673 | −0.037    | 68     | 86      | 29    |
| Meetings     | 8.45%    | 9.10%  | 9.74%    | 10.76% | −2.428 | 0.017 | −0.153    | 78     | 69      | 36    |
| Testing      | 10.96%   | 11.97% | 11.36%   | 13.72% | −0.205 | 0.838 | −0.014    | 74     | 85      | 24    |
| Email        | 7.93%    | 7.77%  | 8.59%    | 12.10% | −0.705 | 0.482 | −0.063    | 72     | 85      | 27    |
| Breaks       | 5.21%    | 5.20%  | 3.46%    | 4.36%  | 4.705  | <0.001 | 0.387     | 47     | 102     | 33    |
| Code review  | 5.44%    | 6.97%  | 5.01%    | 7.94%  | 0.385  | 0.700 | 0.035     | 56     | 76      | 50    |
| Specification| 5.49%    | 7.49%  | 5.76%    | 9.25%  | −0.194 | 0.847 | −0.016    | 54     | 68      | 61    |
| Learning     | 5.30%    | 7.49%  | 6.07%    | 12.31% | −1.046 | 0.297 | −0.089    | 51     | 76      | 55    |
| Helping      | 4.25%    | 4.87%  | 3.60%    | 6.18%  | 1.664  | 0.098 | 0.128     | 46     | 81      | 57    |
| Administration| 4.70% | 8.14%  | 5.15%    | 9.97%  | −0.706 | 0.481 | −0.051    | 55     | 80      | 47    |
| Interruptions| 3.58%    | 4.81%  | 2.42%    | 3.96%  | 2.814  | 0.005 | 0.263     | 39     | 79      | 62    |
| Documentation| 4.69%    | 9.84%  | 3.77%    | 7.41%  | 1.256  | 0.211 | 0.116     | 50     | 71      | 62    |
| Various      | 3.17%    | 3.97%  | 2.84%    | 6.39%  | 0.590  | 0.556 | 0.051     | 49     | 78      | 56    |
| Networking   | 3.10%    | 4.97%  | 1.60%    | 3.85%  | 4.334  | <0.001 | 0.350     | 31     | 77      | 74    |

Note. t: t-value of a dependent sample t-test; Cohen’s d: standardized mean difference; Higher: Participants who scored higher on an activity at time 2 compared to time 1; Lower: Participants who scored lower at time 2; Equal: Number of participants whose score has not changed.
coefficients of $r \geq .25$ are significant. This is because the $p$-value of $r = .25$ is just below the .0005 threshold for our sample size of 192, $p \approx .00047$.

The correlation coefficients are presented in Table 5 and Table 6. This analysis did not show substantially significant results. At time 1, only productivity was negatively correlated with time spent on breaks, $r = -.30, p = .00002$, which can be considered to validate further our productivity measure rather than a meaningful finding itself. At time 2, none of the correlations was significant at $\alpha = .0005$. The correlation between productivity and time spent on breaks was again negative but did not reach statistical significance, $r = -.16, p = .03$. Overall, we conclude that work activities carried out at home are not related to well-being, productivity, and other variables.

4.3 RQ3: Do the needs for autonomy, competence, and relatedness predict software engineers’ task-specific satisfaction and productivity?

To test the third research question, we run in a first step two linear-mixed models with random intercepts across all tasks using the R-package lme4, version 1.1-25 [4]. A linear-mixed model is superior to a standard multiple linear regression because the responses are not independent, which is an assumption of regression analysis [7]. Each participant responded to three activities, making
them dependent. Ignoring dependencies can result in biases such as an inflated type-I error rate (i.e., false positives) [44]. Figure 2 displays the results. Task satisfaction was negatively predicted by conflicts and pressure, and positively by autonomy, competence, and relatedness. In turn, productivity was only predicted by autonomy, relatedness, and especially competence.

In the next step, we tested whether the pattern of our findings would hold within each of the completed tasks by at least 77 participants. This threshold was used because the power analysis reported above revealed that at least 77 participants were needed to detect a medium effect size. As can be seen in Figure 3, the pattern of the result was mostly consistent across the tasks, but some minor deviations occurred. For example, for meetings, competence did not matter for participant’s task satisfaction and productivity, but autonomy mattered. In other words, during meetings, it matters more whether people have the feeling they are autonomous rather than competent.

4.4 RQ4: Are the associations between task satisfaction and productivity moderated by resilience and company support?

We tested the fourth research question by running a series of 2 (DV: task satisfaction vs. productivity) × 5 (IVs: task-specific variables autonomy, competence, relatedness, conflict, pressure) × 8 (moderators: resilience, leadership, balance, empowerment, enablement, soft-support, hard-support, recognition) = 80 moderated regression analyses. Specifically, we multiplied each of the task-dependent variables with each of the task-independent variables. Given a large number of tests, we set our α-level to .001 to reduce the likelihood of false-positive results. However, none of the interactions reached statistical significance, ps > .001. Together, this suggests that only task-specific variables matter for task satisfaction and productivity.

Additionally, we tested whether any of the seven task-independent variables would be associated with task satisfaction and productivity; we again run two linear-mixed models with random intercepts across all tasks. The predictors were resilience, leadership, balance, empowerment, enablement, soft support, hard support, and recognition. None of predictors reached statistical significance, p > .16.

4.5 RQ5: Do software engineers’ work activities while WFH during the pandemic affects their task-specific well-being, productivity, and psychological needs?

Since our design had left many empty cells, a standard approach such as a within-subject ANOVA was not possible (e.g., no participant reported that they

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8 All graphs were created using the R-packages ggplot2, version 3.3.2 [86], and ggstatsplot, version 0.6.1 [61].

9 Please recall that participants only responded to the top 3 tasks out of a total of 12 possible options, as per survey design.
were networking and doing administrative tasks). We, therefore, standardized all of our seven outcome variables and tested whether tasks would lie above or below the midpoint for each scale using a series of one-sample t-tests. This approach allows testing whether doing a specific task increases or decreases, for example, task satisfaction compared to the average of all tasks. Considering the high number involved in our analysis, we set the new alpha-level to .001,
Fig. 3 Predictors of well-being and activity across tasks with $n \geq 77$. The horizontal lines represent 95%-CIs.
which means that we will only consider results to be significant if $p < .001$ or the 99.9%-CI does not include zero. Results are displayed in Figures 4 and 5 and Tables 7 and 8. Task satisfaction was on average lower when participants were bugfixing [$M = -0.48, SD = 1.02, t(114) = -5.07, p < .0001$], and higher when participants were helping others [$M = 0.56, SD = 0.77, t(35) = 4.39, p = .0001$]. Further, participants experienced higher levels of autonomy when coding and lower levels of autonomy when being in meetings and writing emails. Competence was lower when bugfixing and higher when helping people. Relatedness was only higher when people were helping. Pressure and conflict were not impacted by task.

5 Discussion

5.1 Implications for Research and Practice

Our investigation addresses the need for scholarly evidence concerning the effects of WFH during the COVID-19 pandemic on software developers’ work activities, including the impact on professionals’ well-being and productivity.
Further, a deeper understanding of the effect of the pandemic on professional working life for the large number of software professionals working remotely provides relevant insights for both research and practice. To this end, this study makes several contributions, as summarized in Table 7.

First, we ran an exploratory longitudinal study during the COVID-19 lockdown with 192 carefully selected software professionals to address the first and second research questions. We assessed developers’ working activities and their perceived well-being, productivity, and other relevant psychological and

### Table 7: Differences between tasks

| Task satisfaction | Task productivity | Autonomy | Competence |
|-------------------|-------------------|----------|------------|
| Coding            | 0.048             | 0.875    | 0.345      |
| Debugging         | 0.001             | 0.391    | 0.024      |
| Testing           | 0.015             | 0.110    | 0.115      |
| Specification     | 0.015             | 0.981    | 0.012      |
| Reviewing         | 0.010             | 0.012    | 0.012      |
| Documenting       | 0.001             | 0.020    | 0.020      |
| Meetings          | 0.006             | 0.002    | 0.002      |
| Emails            | 0.011             | 0.001    | 0.001      |
| Learning          | 0.020             | 0.020    | 0.020      |

Note: Each entry was first standardized. We then performed a series of one-sample t-tests to test whether participants were on average above or below 0.5 (i.e., the average across all tasks) for each task and variable.
social variables. Our data quality was assured by the high test-retest reliability of each variable measuring at least .50, and Cronbach’s alpha values above .60. Second, we compared the time spent on typical office-based working activities with the same activities while working from home. Using the taxonomy and previously collected data of Meyer et al. [56], we ran 30 one-sample t-tests to assess significant differences. Although we reported several differences, they are relatively small, which indicates that the time spent on different activities is almost identical in both the online and the physical working environment. Third, we analyzed whether the time spent on each working activity changed during the pandemic. After performing 15 paired t-tests, we conclude that developers did not change how they spend their time during the mandated working from home period. Fourth, we investigated whether well-being-related variables and productivity are associated with the time spend on each activity and if the findings replicate across both time points. To do so, we ran twice 195 correlation analyses. Our results suggest that well-being-related variables and productivity are not associated with the time spend on each activity. However, a shortcoming of our exploratory study is that we only measured general well-being, productivity, and needs, as well as the amount of time spent on various tasks during the past week. The lack of significant findings could suggest that either the type of task does not impact professionals’ well-being and productivity or that many other factors impact well-being and productivity more strongly (e.g., quality of social contacts [69]). We found evidence for the former in our confirmatory study.

In our confirmatory study, we tested whether task-specific variables, such as the need for autonomy, competence, relatedness, and task-independent variables, such as resilience or empowerment, are associated with task satisfaction and productivity third research question. Additionally, we tested whether task-specific and task-independent variables interact in predicting task satisfaction and productivity, addressing the fourth research question. Finally, we tested whether specific tasks impact professionals’ task-specific satisfaction and productivity, addressing the fifth and final research question.

Table 8 Differences between tasks (continued)

Note. Each variable was first standardized. We then performed a series of one-sample t-tests to test whether participants score on average above or below 0 (i.e., the average across all tasks), separately for each task and variable.
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RQ1: Has the distribution of daily working activities of software engineers changed while WFH during the pandemic as compared to pre-pandemic daily working activities? On the whole, we did not register significant changes to developers’ work distribution. Further, we highlight that Meyer et al.’s sample covers only one software company (Microsoft) [56], whereas we surveyed developers across many companies globally distributed. Therefore, some deviations were expected. Nevertheless, we still report an overall consistency between our WFH data and Meyers et al.’s analysis of a typical office day at Microsoft. Our results show that working from home does not affect how software engineers dedicate their time to specific tasks. However, we observed some minor differences. Most notably, software engineers spend less time on bugfixing, meetings, and breaks. Also, they report less time on e-mail writing (only in wave 1) and fewer interruptions when working from home (only in wave 2). Contrary, they spend more time on specifications, testing, administration, documentation, and learning. It is unclear whether those minor differences emerged because of the pandemic or because our sample differed.

We observe that meetings are significantly reduced while working remotely. One explanation is that they are, on average, shorter and more time-efficient than in the office. Also, our participants invested in improving their skill set as they spend more time learning. Similarly, developers seem to be more focused on their tasks, considering fewer reported breaks and interruptions. However, this does not mean that they are not linked to their organization or their colleagues since the time spent on networking remained the same. This cautiously suggests that WFH might be more beneficial for both developers and organizations than working in the office, or at least for some group of professionals [28]. However, while some studies support our conclusion that WFH increases or does not impact productivity [2,19,69], some studies also found that WFH has a negative impact on productivity [33,45,59]. As there are too many potential differences between the studies (e.g., cultural factors, working conditions at home, type of work, measurement of productivity), we need to wait for cross-country and cross-profession studies with large sample sizes or meta-analyses that synthesize the findings to get a better idea as of why some studies found that WFH did not impact productivity during the Covid-19 pandemic. In contrast, other studies found a negative impact. We did not register any significant change in the work activities during our exploratory investigation, with only two exceptions: at the first wave, developers spent more time on breaks and networking than during the second wave. Nevertheless, we report a correlation close to 1 of the group averages, suggesting a very high consistency in the pandemic activity distribution. The reason software engineers spent less time on breaks and networking during the second measurement point might indicate that they became more accustomed to their new WFH condition. Accordingly, professionals learned to spend their working time more efficiently. Similar conclusions are also supported by the literature [29,69].

RQ2: Is the distribution of daily working activities related to well-being, productivity, and other variables? We did not find any significant relationships except for one concerning our extensive correlation analysis between working
activities and potentially relevant variables. This can be interpreted as a generally positive finding. It shows that various tasks are unrelated to important psychological and social variables while WFH is measured typically (e.g., well-being over the past week). The only significant relation was productivity, which correlated negatively with breaks in wave 1. Despite being intuitive, we are very cautious about concluding that developers should take fewer breaks to be more productive since such a relation was not significant at wave 2 (although still negative). This is also because breaks can increase well-being \[16\] and breaks can also improve the quality of professionals’ social networks \[82\]. Also, correlation does not equate causation: Participants might have taken more breaks because they felt less productive for various reasons (e.g., more exhaustion, distractions at home). Regarding the other activities, we conclude that the time spends on each task does not affect productivity or well-being. We did not register any significant effect on how the amount of time dedicated to development activities impacts software engineers’ general well-being, stress, boredom, or distractions while working from home. Previous studies showed that during the pandemic, it is essential to have daily routines to improve personal well-being \[69\]. However, when it comes to individual activities, routines seem not to play a significant role. Regardless of how software engineers organize their day, this does not affect the time they dedicate to one activity. Likewise, possible distractions that might happen while working from home (e.g., children at home) do not influence the time spent on work activities.

Self-determination theory measures innate psychological needs \[71\], and its three dimensions, need for autonomy, competence, and relatedness, are associated with work motivation in general \[31\]. To the best of our knowledge, our study is the first in our community to assess whether specific activities are correlated with autonomy, competence, and relatedness. We found overall that general psychological needs were unrelated to people’s specific activities. In hindsight, this might be because the scale we used to measure the three dimensions of the self-determination theory captures broad human needs in general \[71\] and not specifically while working on specific tasks. We addressed this limitation of the exploratory study in the confirmatory analysis.

While working remotely, the quality of communication can be challenging, as face-to-face communication has to pass through a medium (e.g., MS Teams, Zoom). Not being directly connected to the organizations can, therefore, become a big issue for remote workers. For example, research suggests that lower support from coworkers and supervisors \[53\], perceiving the values of one’s organization to be different from one’s values \[23\], and unfair treatment and lack of appreciation \[6\] are putting the mental health of remote workers at risk. Interestingly, our results suggest that the quality of communication does not relate to individual working activities, which is surprising at first glance given that it is plausible to assume that those who find the quality of communication poorer might engage less in activities that require more communication (e.g., meetings) and more in activities that require less communication typically (e.g., coding, bugfixing). This can also be considered a positive finding, as the time spent by software engineers for each task is not detrimental to the relations
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with their organization. Prior research has mostly ignored whether activity type plays a role in professionals’ psychological and social factors. Typically, scholars only measured whether people are, for example, overall stressed, as opposed to stressed by specific activities [6,23,53]. Our research suggests that the type of activity is not a confounding variable, which increases our trust in prior research, which has typically looked at subjective work experience in general rather than actual activities. So, our exploratory findings suggest that software engineers’ psychological and social factors do not matter on what work activity they are performing, but rather how it is done.

RQ3: Do the needs for autonomy, competence, and relatedness predict software engineers’ task-specific satisfaction and productivity? In the confirmatory study, we found, across all tasks, that the need for autonomy, competence, and relatedness was positively associated with task satisfaction and productivity. Simultaneously, conflict was negatively associated with the need for autonomy, competence, and relatedness. Pressure was only negatively associated with task satisfaction but was unrelated to productivity. These associations were mostly consistent across tasks, albeit a few deviations occurred (Fig. 3). For example, task relatedness predicted task productivity for meetings and reviewing, but not for coding, bug fixing, testing, and learning. One possibility is that meetings and reviews are typically more social (i.e., done with other people), making relatedness more relevant.

This result is of great relevance to understanding developers’ productivity. To improve task satisfaction and productivity, self-determination theory is a precious lens. Indeed, more autonomous, competent, and related professionals show a high degree of satisfaction and productivity. These findings are also incredibly valuable for employee recruitment and retention. Companies should keep this aspect in mind when organizing working tasks. In particular, micro-management could be detrimental to software engineers’ satisfaction and productivity. In other words, it is advisable to discuss realistic working goals of software projects, leaving it to the teams to self-organize, like a recent investigation about effective Scrum teams highlighted [81].

RQ4: Are the associations between task satisfaction and productivity moderated by resilience and company support? None of the seven task-unrelated variables (e.g., resilience, work-life balance) did moderate the link between the three needs and task satisfaction and productivity. Initially, we hypothesized that, for example, resilience might buffer against reduced autonomy because resilient people are more likely to ‘bounce back after stressful events such as being less able to make autonomous decisions [76,85]. This might be because we measured resilience and work-life balance in a way that is too broad. Generally measured variables (e.g., general work-life balance) are rarely associated with specific variables [13]. Future research could measure resilience in a more specific way (e.g., resilience during the day or task-specific resilience), which makes it more relevant for task-specific satisfaction, productivity, and basic needs.

Additionally, caring leadership, work-life balance, empowerment, job enablement, soft company support, hard company support, and recognition were
unrelated to task-specific satisfaction and productivity. This is not surprising given that we measured all these variables generally. If we had measured task-life balance instead of general work-life balance, for example, we would have likely found an effect on task-specific satisfaction and productivity.

Overall, our results are inconclusive on this question. Although the moderation effects of resilience and company support are not supported, we acknowledge that with more specific measurements, this outcome might change.

**RQ5**: Do software engineers’ work activities while WFH during the pandemic affect their task-specific well-being, productivity, and psychological needs?

We found that task satisfaction was relatively lower when participants were bugfixing and higher when they were helping others. This finding is in line with previous research suggesting that helping others increases well-being [9]. In contrast, levels of task productivity were more consistent across tasks, while task satisfaction varied.

Our findings that bugfixing is associated with lower and helping with higher task satisfaction have important practical implications. First, bugfixing might be viewed as an annoying but necessary task by developers. Pointing out the meaningfulness of bugfixing is essential. Literature supports that meaning is positively associated with satisfaction, autonomy, competence, and relatedness [51]. Additionally, organizations should support a higher degree of socialization during bug fixing activities. Software engineers appear to be (contrary to stereotypes) social and caring individuals. Consequently, code review practices should be primarily supported by management. Second, organizations should facilitate an inclusive working environment where developers are actively helping each other to perform different tasks they can freely choose from. One concrete example might be to establish innersourcing projects [77]. They are similar to open source projects, except that they are closed projects in which only employees can participate. This practice would also support the need for autonomy of software professionals in contributing to projects they find important and committed to. Third, establishing mentorship programs can stimulate senior developers’ desire to help by increasing newcomers’ sense of relatedness. This aspect is even more important in a WFH setting, where informal networking occasions are typically limited. At the same time, this will increase the onboarding success of new employees. Research already showed that the support of newly hired employees through, for example, mentoring projects, is the most important factor for onboarding success and, eventually, employees’ retention [72].

5.2 Measuring satisfaction and productivity

Together, findings from both studies have not only practical but also methodological implications. General measures of personality, needs, or working conditions are not associated with how much time software engineers spend on a specific task or how satisfied or productive they are while doing a task. Researchers or employers who wish to identify how to increase satisfaction or
productivity of a specific task need to measure task-specific variables rather than general variables. For example, increasing employees’ general resilience or work-life balance will have little impact on how satisfied and productive they are with a specific coding task. In contrast, enhancing autonomy is likely more beneficial.

However, this does not imply that general measures of personality and other constructs cannot predict task-specific variables. Previous research established that, for example, personality variables predict related behavior averaged over a sample of occasions and situations much better than single observations [24,74]. This is because general measures are broad and trans-situational by definition. For instance, resilience is important in many aspects of a software developer’s life, not only while they are coding on a specific day. This activity, in turn, can also be influenced by many situational variables (e.g., distractions at home, a particular project, working with competent colleagues) that diminish the impact of personality. If researchers are interested in testing whether, for example, resilience predicts task satisfaction, they might want to measure task satisfaction across multiple tasks (e.g., coding, bugfixing) and/or multiple time-points [5].

5.3 Threats to validity

To conclude this section, we briefly address the most relevant limitations.

Reliability. We investigated our subject matter using a longitudinal exploratory design combined with a confirmatory cross-sectional one. Participants were identified using a multi-stage selection process to ensure (i) they are professionally active software engineers, (ii) data quality, and (iii) that they were working from home during the lockdown. Validated scales have been used when available or adapted from previous investigations. Overall, we report a high test-retest reliability in the longitudinal study and adequate internal consistencies of all measures.

Construct validity. To enhance cross-study comparability, we used the taxonomy by Meyer et al. [56] to define the daily activities of software developers. Similarly, we used those benchmarks to confront it with working from home settings. However, we did not monitor developers’ effectiveness by executing every task while working remotely. We opted for this to be consistent with Meyer et al. and because we collected data from a global sample of software professionals working in 190+ different organizations, making the development of objectively comparable measurements near impossible. Still, we report some differences with the data collected by Meyer et al., although the difference is of only some percentage points.

Conclusion validity. Our conclusions rely on multiple statistical analyses, such as one-sample t-tests, paired t-tests, Pearson’s correlation, multiple regressions, and linear mixed-effects models. Furthermore, we also ran a non-parametric Spearman’s rank correlations test for our conclusion’s consistency since not all distributions were perfectly normally distributed. To support
| Findings | Implications |
|----------|--------------|
| Has the distribution of daily working activities of software engineers changed while WFH during the pandemic: as compared to pre-pandemic daily working activities? | Overall, the ranking among work activities remains mostly unchanged. However, when WFH developers spend less time in: Bugfixing ($t_1 = -5.11, t_2 = -3.55$), Meetings ($t_1 = -9.95, t_2 = -6.63$), Breaks ($t_1 = -7.39, t_2 = -14.36$), Interruptions ($t_1 = -5.39, E=4.69$), and more time in Specification ($t_1 = 4.65, t_2 = 4.65$), Training ($t_1 = 3.41, t_2 = 3.32$), Administration ($t_1 = 4.58, t_2 = 4.28$), Documentation ($t_1 = 5.18, t_2 = 5.07$), Learning ($t_1 = 4.24, t_2 = 3.36$). Additionally, we found very high correlation of the group averages of time 1 and 2 ($r(13) = .99, p < .0001$). A series of 15 paired t-tests comparing the relative time spend on each of the 15 activities between time 1 and 2 found little change. Two exceptions were more Breaks ($t = 4.71$) and Networking ($t = 4.33$) at time 1 compared to time 2. |
| Is the distribution of daily working activities related to well-being, productivity, and other variables? | A series of 2 × 195 correlation analyses did not show substantially significant results. Overall, we conclude that work activities carried out at home are not related to well-being, productivity, and other variables. |
| Do the needs for autonomy, competence, and relatedness predict software engineers’ task-specific satisfaction and productivity? | In the confirmatory study, we found, across all tasks, that the need for autonomy, competence, and relatedness was positively associated with task satisfaction and productivity, using linear mixed-effects modeling and multiple linear regression analysis. Simultaneously, conflict was negatively associated with the need for autonomy, competence, and relatedness. Presence was only negligibly associated with task satisfaction but was unrelated to productivity. These associations were primarily consistent across tasks, albeit a few deviations occurred (Fig. 1). |
| Are the associations between task satisfaction and productivity moderated by resilience and company support? | A series of 80 moderated regression analyses revealed that neither caring leadership, work-life balance, empowerment, job satisfaction, or company support, nor recognition moderates the link between the three needs and task satisfaction and productivity. Additionally, all seven task-unrelated variables were unrelated to task-specific satisfaction and productivity. We found that task satisfaction was relatively lower when participants were bugfixing and higher when they were helping others, using a series of 84 one-sample t-tests. Additionally, autonomy was perceived lower while professionals were helping others in meetings or writing emails. Competence was higher when professionals were helping others and lower when bugfixing. Relatedness was higher when professionals were helping others. The findings held even after controlling for multiple comparisons. |
| Do software engineers’ work activities while WFH during the pandemic affect their task-specific well-being, productivity, and psychological needs? | This can be interpreted as a generally positive finding, as it shows that various tasks are unrelated to important psychological and social variables while WFH if they are measured typically (e.g., well-being over the past week). Self-determination theory provides a robust framework to understand and enhance developers’ productivity and well-being. A higher degree of autonomy, competence, and relatedness for software professionals can increase their satisfaction and productivity. Rather than control or micro-management, organizations should support employees to tailor their own working tasks and training. |

Our results are inconclusive. Possibly, with more specific measures, this outcome might change. As a community, we need better and more nuanced measurements of satisfaction and productivity in order to identify specific factors that contribute to professionals’ satisfaction and productivity compared to overall assessments. Repeated self-reports (e.g., Experience Sampling [47]) can identify the effect of contextual factors (e.g., current task). This allows for collecting reliable and contextually rich data as participants assess their current state rather than reflect on an extensive time in the past [39].

Breakfast is associated with lower task satisfaction while helping improves it. Code review, in-person training, and mentoring projects support software engineers’ desire to help, making them more satisfied and productive. At the same time, more junior figures can learn from more experienced ones, increasing employees’ retention.

Open Science, we make a reproducible R-code alongside our raw data openly available on Zenodo.

Internal validity. We used self-reported measures for well-being, productivity, and other psychological and social variables for this investigation, which might be considered a limitation. The data was collected towards the end of the first lockdown in spring 2020 with a longitudinal design. We expanded our initial
data collection one year later, in spring 2021, with a cross-sectional study. This enabled our participants to report a more mature and stable assessment of the new working setting. For the exploratory investigation, we only considered countries with comparable lockdown measures (e.g., we excluded, among others, Denmark, Germany, and Sweden as these countries did not face a total lockdown or had different measures in place in the country’s regions). Thus, we asked both waves about lockdown conditions in their home country and if they were still working from home. Since all selected informants faced comparable conditions, we did not exclude any of the 192 selected software professionals. For the confirmatory study, we surveyed 300 developers working from home. Since lockdown measures in spring 2021 were comparable across all countries, we did not exclude any country a priori.

**External validity.** We designed this study to maximize internal validity. Therefore, we determined our sample size with an a priori power analysis. So, we did not work with a representative sample of the software engineering population in mind (such as Russo and Stol [70] did, where the research goal was to generalize results, surveying over 400 software engineers). However, we recognize having submitted our surveys in the middle of a very peculiar period. This makes it unclear whether we can generalize our findings to non-pandemic working from home settings. Notwithstanding, we also realize that we require fast and reliable evidence regarding the COVID-19 crisis we are facing right now, improving the quality of developers’ daily lives. This study will also enable a better-informed research design for future remote working studies once this pandemic is over.

### 6 Conclusion

This research focused on software engineers’ task satisfaction and performance during the COVID-19 pandemic. To do so, we first employed an exploratory longitudinal study design across two waves and a confirmatory cross-sectional study. We found that developers still spend proportionally the same amount of time on their different daily activities. For example, the software engineers in our sample still spent most of their working time on coding, bugfixing, meetings, testing, and e-mails, as previously reported by Meyer et al. [56]. Nevertheless, we found some significant mean differences. Our participants reported having spent less time in meetings and breaks, suggesting that both were less common, possibly due to developers’ adaption of working remotely. Similarly, no significant relations have been found between productivity, well-being, and relevant social and psychological variables with working activities. In our confirmatory cross-sectional study, we found that task-specific needs for autonomy, competence, and relatedness are associated with task-specific satisfaction and productivity. Furthermore, task satisfaction was relatively lower when participants were bugfixing and higher when helping others. At the same time, autonomy was perceived as relatively lower while professionals were in meetings or writing e-mails.
Overall, our research suggests that WFH does not per se affect how much time developers spend working on various tasks. Nevertheless, software engineers are social beings, and their satisfaction and productivity increase when they can help others. This paper also suggests a number of recommendations for organizations to support their employees’ well-being and productivity.

Future research should aim to provide more tailored recommendations based on developers’ persona. This would result in a more nuanced understanding of the subject matter. Also, a better understanding of software professionals’ task satisfaction and productivity is needed to develop reliable measurement instruments, leading to better theories.

Supplementary Materials

The complete replication package is openly available under CC BY 4.0 license on Zenodo, DOI: [https://doi.org/10.5281/zenodo.4897936](https://doi.org/10.5281/zenodo.4897936)

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