

The Cognitive Cost of Going the Extra Mile: How Striving for Improvement Relates to Cognitive Performance

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Organizations are increasingly expecting individuals to engage in task proactivity, that is, to find better ways of doing their job. While prior research has demonstrated the benefits of task proactivity, little is known about its cognitive costs. To investigate this issue, we build theory on how task proactivity affects end-of-day cognitive performance. We propose that task proactivity involves deviating from established ways of working and engaging in cognitively demanding activities requiring high levels of mental effort, which manifest as an erosion of end-of-day cognitive performance. In two daily diary studies, we found that individuals engaging in task proactivity experience lower end-of-day cognitive performance (Study 1 over five consecutive workdays: $n = 163$, $k = 701$; Study 2 with multiple daily assessments over seven consecutive workdays: $n = 93$, $k = 471$), even when controlling for task performance (Study 1) and beginning-of-day cognitive performance (Study 2). In two experiments, we then show that simulating task proactivity results in greater mental effort and lower routineness but not in greater ego depletion (Study 3: $N = 318$ and Study 4: $N = 319$) or increased self-control demands, -effort, or -motivation (Study 4). This provides support for our proposed cognitive pathway. Our findings enhance our understanding of the cognitively demanding nature of task proactivity and provide empirical support for its cognitive costs using a mental fatigue lens. They also suggest that the impact of a cognitively demanding activity like task proactivity may persist throughout the day and carry over to other tasks involving cognitive performance.

Keywords: task proactivity, mental fatigue, cognitive performance, routines, daily diary study

Supplemental materials: <https://doi.org/10.1037/apl0001199.supp>

Everyone now has two jobs. First, to build the car. Second, to find ways of doing the job better.

—John Towers (Caulkin, 1993)

Given the growing complexity and uncertainty in today's work environment, organizations increasingly expect individuals not only

to fulfill their prescribed job requirements but also to find better ways of doing their job. Research has demonstrated that people indeed frequently attempt to find new and/or more efficient ways of doing their job, such as by introducing and applying new ideas (e.g., Wu et al., 2014), by identifying problems and preventing them from recurring (e.g., Barclay & Kiefer, 2019), by redefining their tasks

This article was published Online First May 23, 2024.

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This research was supported by grants from the German Research Foundation (Grant FA 458/5-1) awarded to Doris Fay as well as by grants from the French National Research Agency (ANR-16-FRAL-0005-01) and the ESSEC Research Center awarded to Karoline Strauss. The authors have no known conflicts of interest to disclose.

The authors are grateful to Sarah Brassat, Frances A. Hebestadt, and Egwen Kervizic for their help in the data collection. The authors are also grateful to Sabine Sonnentag, Uta Bindl, and Jung Won Lee for their insightful comments on an earlier version of the article. This article is partly based on El Mansouri's doctoral dissertation, completed in 2022 under the guidance of Karoline Strauss.

A previous version of this article was presented at the 80th Annual Meeting of the Academy of Management in 2020, and its abstract was published in the Academy of Management Proceedings. Another part of the article was presented at the 79th Annual Meeting of the Academy of Management in 2019 as part of a symposium.

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Mouna El Mansouri played a lead role in conceptualization, data curation, formal analysis, investigation, methodology, project administration, software, visualization, and writing—original draft and an equal role in writing—review and editing. Karoline Strauss played a lead role in conceptualization, funding acquisition, and supervision, a supporting role in formal analysis, investigation, methodology, and writing—original draft, and an equal role in resources and writing—review and editing. Doris Fay played a lead role in funding acquisition, a supporting role in investigation and methodology, and an equal role in resources and writing—review and editing. Julia Smith played a supporting role in data curation and project administration.

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(e.g., Staw & Boettger, 1990), and by designing strategies to organize their work or adopting new technologies (e.g., Bruning & Campion, 2018). Across different research areas, scholars have demonstrated that individuals make improvements to the way their core tasks are done (i.e., individual task proactivity; Griffin et al., 2007) and that finding more efficient ways to do one's job entails many benefits (e.g., in terms of individual and firm performance, mastery, adaptivity, innovation, engagement; Baer & Frese, 2003; Barclay et al., 2022; Tornau & Frese, 2013; Zacher et al., 2019).

Yet, task proactivity, or improving the way one's core tasks are performed (Griffin et al., 2007), involves deviating from established ways of working. From a cognitive perspective, however, sticking to established ways of performing one's job reduces mental effort (Ohly et al., 2006, 2017). When tasks have been executed repeatedly, they become habitual (Betsch et al., 2001) and thus less cognitively demanding (Kanfer & Ackerman, 1989; Norman & Bobrow, 1975; Ohly et al., 2006, 2017). Conversely, completing tasks in a new way implies increased cognitive demands (Kanfer & Ackerman, 1989). Experimenting with more efficient ways of accomplishing one's tasks may thus entail cognitive costs. Yet, the literature has, to date, not considered this possibility.

To explore these potential cognitive costs of task proactivity, we draw on research on cognitive demands and mental fatigue and build theory on how end-of-day cognitive performance is affected by individuals' efforts to find new, more efficient ways of performing their tasks. We consider that task proactivity requires individuals to deviate from routine execution and engage instead in a host of cognitively demanding activities such as information processing, analysis, reasoning, and learning from trial and error. Task proactivity thus implies increased cognitive demands as well as increased efforts geared towards meeting these demands. As a result, mental fatigue increases and manifests itself as eroded performance in cognitively demanding tasks that take place later in the workday (Danziger et al., 2011; Linder et al., 2014). In short, we propose that as individuals exert mental effort as part of their task proactivity, they may experience greater mental fatigue and, thus, a deterioration of their end-of-day cognitive performance.

To investigate the relationship between task proactivity and subsequent cognitive performance, we conducted two daily diary studies assessing daily task proactivity as well as end-of-day performance in a cognitive task. Study 1 aims to establish the link between task proactivity and cognitive performance. Study 2 aims to replicate the findings of Study 1 and enhance confidence in the temporal ordering of the variables. To reduce individual biases related to self-reporting, we administer the "*n*-back task," an objective cognitive task extensively used by researchers in lab settings to examine cognitive performance (Jaeggi, Buschkuhl, et al., 2010; Jaeggi, Studer-Luethi, et al., 2010). Performance in cognitive tasks such as the *n*-back task has been consistently used as indicator of the underlying cognitive functioning level of individuals (Hockey, 1997; Kahneman, 1973). We administer this cognitive task as part of our ambulatory assessment. This enables us to assess cognitive performance while participants remain embedded in their natural life contexts (Bolger & Laurenceau, 2013; Ohly et al., 2010). Studying cognitive performance in this novel way, including an objective measure in a daily diary study, allows us to examine the relationship of task proactivity with individuals' cognitive functioning in realistic conditions. In Study 3, a preregistered experiment, we then manipulate task proactivity and examine its effect on the proposed

mechanisms of increased mental effort and reduced routineness. In Study 4, we contrast these proposed mechanisms with a key competing theoretical mechanism: increased self-control demands and resulting ego depletion.

We contribute to the literature in several ways. First, we contribute to research on the outcomes of proactivity by investigating its potential drawbacks and resource-intensive nature. While finding more efficient ways to complete one's tasks undoubtedly has benefits (Baer & Frese, 2003; Barclay et al., 2022; Tornau & Frese, 2013; Zacher et al., 2019), it may also entail cognitive costs. Prior research has speculated about potential costs of proactivity for individuals (Belschak et al., 2010; Bolino et al., 2010) but has empirically focused primarily on affective and social mechanisms and outcomes. For instance, Cangiano et al. (2019) argued that proactive behavior would be associated with anxiety because of its uncertain outcomes and "risky nature," a hypothesis not supported by their data. Fay and Hüttges (2017) found daily proactive behavior to be linked with higher daily cortisol levels, presumably because it is accompanied by frictions with colleagues. Sun et al. (2021) demonstrated that employees with a predisposition for engaging in proactive behavior become the target of coworkers' upward social comparisons, leading to envy and undermining. While there is thus evidence for the social and affective costs of proactive behavior, its cognitive costs have received little attention to date.

We contribute to the literature by clarifying the mechanism underlying the resource-intensive nature of proactivity. Theoretical work has hinted at the possibility that proactivity may be "depleting" (e.g., Bateman, 2017; Bolino et al., 2010), and scholars have suggested that proactivity may involve resource-intensive higher order cognitive processes (Strauss et al., 2017) as well as self-control resources (Grant et al., 2011; Strauss et al., 2017). However, these mechanisms have not been tested. By focusing on the cognitive demands resulting from task proactivity and ruling out increased self-control demands and resulting ego depletion as an alternative theoretical explanation, we provide evidence for the cognitively demanding nature of proactivity. This is important because of the potential impact on cognitive processes such as decision making and reasoning (Danziger et al., 2011; Linder et al., 2014). Hence, we enhance our understanding of the demanding nature of task proactivity and provide empirical support for its cognitive costs using a mental fatigue lens.

We further contribute to research on cognitive performance in organizational contexts, specifically by exploring whether the effects of cognitive demands may persist over time. Prior laboratory experiments have highlighted a decline in cognitive performance following cognitively demanding tasks (Lavric et al., 2000; Norman & Bobrow, 1975), but such drops in performance were considered as rather immediate and temporary in nature (Baddeley, 2003; Barrouillet et al., 2007; Wickens, 1991). Studies outside of laboratory settings suggest, however, that cognitive performance may suffer not only temporarily with fast recovery. Instead, the effects of cognitive demands persist over the course of the day. For example, Danziger et al. (2011) focused on decision making over the course of a day and its cumulative impact on the nature of rulings by judges. They showed that judicial rulings happening later in a sequence of cases had a greater probability of rejecting prisoners' requests. The authors argue that this is due to mental fatigue after repeated decision making. Similarly, Linder et al. (2014) suggested that continuing cognitive demands (mainly decision making for

several hours) lead clinicians to make the wrong choice of prescribing unnecessary antibiotics. Our studies build on and expand this perspective and explore the relationship between task proactivity and subsequent cognitive performance. Prior studies of cognitive performance focused either on immediate effects in laboratory studies (Barrouillet et al., 2007; Wickens, 1991) or on domain-specific outcomes (e.g., judiciary rulings, medical prescriptions; Danziger et al., 2011; Linder et al., 2014). By focusing on evening cognitive performance, we seek to establish that the effect of a cognitively demanding work activity may persist throughout the day to an extent that it is associated with cognitive performance at the end of the day and that this link is also demonstrable in a generic measure of cognitive performance that is not related to the cognitively demanding work activity.

Theoretical Framework and Hypothesis Development

A range of concepts have been proposed that relate to employees' efforts to find ways to "do the job better." We focus on task proactivity, behavior aimed at finding better and more efficient ways of doing one's job (Griffin et al., 2007). It is distinct from other related concepts such as creative and innovative behavior, task revision, and task-oriented job crafting. While task proactivity refers to improving the way tasks are accomplished, this may not necessarily involve creativity (i.e., generating novel and useful ideas; Amabile, 1988) or innovation (i.e., implementing these creative ideas; Amabile, 1988) because task proactivity can also involve already established solutions. Task proactivity is also different from task revision, which occurs when individuals uncover misspecified or faulty ways of accomplishing a task and attempt to correct them (Staw & Boettger, 1990). Contrary to task revision, task proactivity does not necessarily focus on correcting erroneous routine tasks but rather involves changing how tasks are executed to bring improvement. Finally, task proactivity is distinct from task-oriented job crafting. Task proactivity is focused on performing core tasks in a better way in order to increase efficiency and performance in one's prescribed role. Task-oriented job crafting, on the other hand, involves redesigning or altering the boundaries of one's tasks in order to optimize person-job fit and experience job meaningfulness (Tims et al., 2016).

Because of its focus on core tasks, task proactivity is likely to be relevant across a range of different work roles and situations (Griffin et al., 2007). For example, an employee may compile a list of answers to frequently asked questions to provide to prospective clients, or a nurse may find a more efficient way of administering medications (Griffin et al., 2007). Studies have used Griffin et al.'s (2007) measure of task proactivity in a large number of occupations and contexts (e.g., employees of a real estate development company in China in Ma et al., 2020; startup employees in India in Sengupta et al., 2021; police officers and police support staff in the United Kingdom in Strauss & Parker, 2018). Across different contexts, task proactivity thus captures employees' attempts to find better ways of doing their job.

The Cognitive Demands Brought by Task Proactivity

In organizational contexts, individuals deal with their regular tasks mostly following prescribed or agreed-upon ways. By repeatedly executing a given task in the same way, individuals automatize the skills and steps needed to perform that task, turning it

into a task routine. Completing task routines entails low cognitive demands because routines are performed in an automatic, proceduralized, and proficient way (Kanfer & Ackerman, 1989; Norman & Bobrow, 1975; Ohly et al., 2006, 2017). This means that task routines allow individuals to save mental effort and, as such, are very beneficial in terms of cognitive functioning (Ohly et al., 2006, 2017).

However, any improvement in how tasks are performed requires individuals to deviate from such routines. While task proactivity will likely bring greater efficiency in the long run, forgoing habitual ways of accomplishing one's tasks means that, in the short term, individuals lose the cognitive gains inherent to routines.

By the same token, as individuals experiment with new and more efficient ways to perform their core tasks, they engage in a host of cognitive processes (Bindl et al., 2012; Frese & Fay, 2001; Sonnentag & Starzyk, 2015) that entail elevated cognitive demands. For example, individuals may analyze their habitual way of working, identify areas of potential improvement, and define expected future benefits (i.e., engage in issue identification, goal setting, and information collection; Frese & Fay, 2001; Sonnentag & Starzyk, 2015). They may imagine different scenarios for how to improve their core tasks, decide about a specific course of action, and plan the steps needed to implement it (i.e., engage in envisioning and planning; Bindl et al., 2012; Frese & Fay, 2001). Individuals may then execute their plan, engage in action control in order to remain on track, and persist while bringing about changes to their core tasks (i.e., engage in enacting and implementation; Bindl et al., 2012; Sonnentag & Starzyk, 2015). Finally, they may engage in information-processing, comprehension, and learning from trial and error to understand the outcomes and implications of their task proactivity and potentially modify or fine-tune subsequent approaches to their core tasks (i.e., engage in reflecting and feedback; Bindl et al., 2012; Frese & Fay, 2001).

All these cognitive processes that task proactivity entails involve elevated cognitive demands. Task proactivity is thus associated with increased mental effort and a deviation from established routines.

Mental Fatigue and Cognitive Performance

The cognitively effortful process of task proactivity is, in turn, likely to result in mental fatigue (Borrágán et al., 2017; Trejo et al., 2015). Mental fatigue is defined as a deterioration in the cognitive performance resulting from cognitive demands (Ishii et al., 2014). Mental fatigue is different from the subjective experience of "feeling fatigued," even though they are sometimes, but not always, related to each other (Ackerman & Kanfer, 2009; Hockey, 2011). Whereas feeling fatigued involves motivational factors that may manifest in the absence of cognitive performance deterioration (Ackerman & Kanfer, 2009), mental fatigue reflects actual cognitive performance decrements. Therefore, the consequences of the cognitive processes involved in task proactivity are most appropriately described in terms of mental fatigue.

Studies conducted in the laboratory demonstrated that manipulating mental fatigue is associated with impaired cognitive performance. For example, in a lab setting, van der Linden, Frese, and Meijman (2003) showed that, compared to nonmentally fatigued participants, mentally fatigued participants experienced difficulties in focusing attention and planning. In another lab study, van der Linden, Frese, and Sonnentag (2003) showed that mentally fatigued participants experienced difficulties in adapting strategies and engaging in more

cognitively demanding exploration to deal with adverse outcomes. In both studies, mental fatigue was linked with errors and suboptimal performance in cognitive tasks.

The Relationship of Task Proactivity With Cognitive Performance

Thus, previous research shows that mental fatigue manifests in impaired cognitive performance. We argue that task proactivity entails cognitive demands, which result in mental fatigue. This assumption is aligned with previous research indicating that cognitive demands result in mental fatigue. Specifically, studies outside a laboratory setting further demonstrate that mental fatigue increases throughout the day as individuals engage in cognitively demanding tasks. A study in primary care (Linder et al., 2014) suggests that cognitive demands (mainly decision making) resulted in increasing mental fatigue throughout a clinic session: Over time, the cognitive performance of clinicians deteriorated, and they were more likely to make the wrong choice of prescribing unnecessary antibiotics. In another setting, Danziger et al. (2011) showed a greater probability of judicial ruling in favor of a prisoner at the beginning of the workday or after a food break. In contrast, judiciary rulings happening later in a sequence of cases were more likely to deny prisoners' requests. The latter is considered as a simplification of decision making, that is, expending less mental effort. The authors argue that this effect results from mental fatigue after repeated decision making as judges use less cognitively effortful strategies by rejecting prisoners' requests as the court session proceeds.

Based on this evidence from the literature, we argue that engaging in task proactivity results in poorer cognitive performance because task proactivity involves elevated levels of cognitive demands, which foster mental fatigue. We hypothesize that:

Hypothesis: Task proactivity during the day is negatively associated with end-of-day cognitive performance.

Competing Theoretical Mechanism: Ego Depletion

Thus far, we proposed that task proactivity will result in poorer cognitive performance because it is associated with increased mental effort and a deviation from routines. Yet scholars have hinted at both cognitive processes and self-control demand mechanisms to explain the presumed resource-intensive nature of proactivity. Bolino et al. (2010) suggested that proactive behavior may deplete resources, including "mental energy" (p. 330). Grant et al. (2011) argued that proactive behavior "often requires self-control and will-power, whereby individuals push themselves to persist in the face of barriers or override the temptation to focus on the short run" (p. 242). Bateman (2017) similarly proposed that the demanding nature of pursuing proactive goals and trying to bring about change "causes resource or ego depletion" (p. 302). Strauss et al. (2017) argued—but did not test—that proactive behavior requires self-control as individuals need to override their impulses and regulate their emotions, as well as higher level cognitive resources (e.g., those involved in anticipation and planning). Thus, there are hints in the literature that proactive behavior may be cognitively demanding as well as requiring significant levels of self-control. Yet research to date has not investigated or disentangled these different

mechanisms, and it remains unclear what specific resources are involved. In order to establish that it is indeed the high levels of mental effort and deviation from routines associated with task proactivity that underlie its relationship with cognitive performance, as we proposed, we therefore aim to rule out ego depletion as a competing theoretical mechanism.¹

Ego depletion describes a state of diminished self-control capacity resulting from prior exertion of self-control (Baumeister et al., 1998). Despite increasing skepticism in the literature based on controversy surrounding the replicability of the ego depletion effect (Carter et al., 2015; Hagger et al., 2016), researchers continue to draw on this theoretical framework (e.g., Lyddy et al., 2021; Tai et al., 2022). Importantly, proactivity researchers have emphasized—but not explicitly tested—the self-control-intensive nature of proactivity (e.g., Bateman, 2017; Strauss et al., 2017), making self-control-related processes an important competing theoretical mechanism. Within the work context, three dimensions of self-control are likely to be required: Individuals need to inhibit spontaneous, impulsive responses, for example, to avoid inadvisable, emotionally charged outbursts (impulse control). They further need to ignore task-irrelevant stimuli (resisting distractions) and overcome their reluctance to complete unattractive tasks (overcoming inner resistances; Diestel & Schmidt, 2011). The process model of ego depletion proposes that exerting self-control will result in shifts in motivational orientation (reduced motivation to exert further self-control and increased motivation to act on impulse) and shifts in attentional focus (reduced attention to addressing discrepancies between actual and desired states and increased attention to rewards; Inzlicht & Schmeichel, 2012).

While it is plausible that task proactivity may involve some level of self-control as individuals need to override the impulse to follow established routines, resist distractions, and potentially force themselves to perform their task in a less appealing way, ego depletion and mental fatigue are two distinct processes (Forestier et al., 2022). Even though both ego depletion and mental fatigue can result in reduced performance in subsequent tasks (Giboin & Wolff, 2019), not all tasks requiring mental effort also require self-control (Forestier et al., 2022). Instead, ego depletion results specifically from resolving a conflict between the person's present desire on the one hand and their higher order goals on the other hand (W. Hofmann et al., 2012).

In order to provide support for elevated cognitive demands as a key mechanism that underlies the effect of task proactivity on subsequent cognitive performance, we include ego depletion as a potential outcome in two experiments (Studies 3 and 4). In Study 4, we also establish that task proactivity does not result in increased self-control demands, reduced self-control motivation, and reduced self-control effort.

Method

Transparency and Openness

We describe in the following sections and in the [Supplemental Materials](#) our sampling plans, data exclusions, and measures for each of our studies. We adhered to the *Journal of Applied Psychology* methodological checklist. Analysis code and research

¹ We are grateful to an anonymous reviewer for this suggestion.

materials are available upon request from the corresponding author. Data are not available due to their proprietary nature. We used Inquisit, Version 5.0.14.0 (Studies 1 and 2) and Version 6.6.1 (reverse causality, laboratory, and online experiments in [Supplemental Materials D, F, and G](#)), to set up and administer the cognitive task (Millisecond Software, 2018, 2022) based on Jaeggi, Studer-Luethi, et al. (2010). We analyzed data using SPSS, Version 28.0, for descriptive statistics and analyses of variance (ANOVAs; IBM Corp., 2021) and Mplus, Version 8.8, for multilevel analyses (Muthén & Muthén, 2017). We used portions of Mplus code by Stride et al. (2015). We did not preregister Studies 1, 2, and 4 (which are presented in the article) and the reverse causality experiment (which is presented in [Supplemental Material D](#)). Study 3 (presented in the article), the laboratory experiment (presented in [Supplemental Material F](#)), and the online experiment (presented in [Supplemental Material G](#)) were preregistered on Aspredicted. Study 1 was part of a broader data collection, for which this is the first publication. Research materials used in Studies 3 and 4 and in the laboratory and online experiments can be found in [Supplemental Material A](#). Measure instructions and adapted items for these studies can be found in [Supplemental Material E](#).

Study 1

Participants, Design, and Procedure

To investigate the relationship between task proactivity and end-of-day cognitive performance, we conducted a daily diary study using a survey sent at the end of the day over the course of five workdays (Beal, 2015; Bolger et al., 2003; Bolger & Laurenceau, 2013). Through a panel provider certified by the International Organization for Standardization ensuring selective recruitment of participants online, we recruited professionals in France who were working full-time under a permanent contract within an organization and with a tenure of at least 1 year in their current position. Participants received a monetary compensation of up to €16, depending on the number of days they participated in the study. The procedures for this study were approved by the ESSEC Research Ethics Committee.²

A total of 434 participants fulfilled our screening criteria, responded to a baseline survey that included demographic characteristics and a cognitive task, and passed a series of attention check items following best practices for online data collection (Cheung et al., 2017). The cognitive task was included in the baseline survey to make sure that participants had installed the necessary software before the start of the daily assessments and that it would operate correctly. Over five consecutive workdays, we then invited these participants to respond to a daily survey, including a cognitive task and measures of our variables. We invited all participants who had completed the baseline survey to participate in the Day 1 and Day 2 surveys. Participants who failed an attention check in the daily survey were not invited for further participation. On Day 3, we invited back only participants who had responded at least on 1 day (i.e., Day 1 or 2); on Day 4, we only invited those who had responded at least on 2 days; and on Day 5, only those who responded on at least 3 days were invited. We used this survey strategy to maximize the number of participants responding on multiple days.

Excluding participants who failed attention check items, our final sample³ consisted of a total of 163 participants (36% retention rate) and 701 days. Seventy participants responded on all 5 days (43%),

72 responded on 4 days (44%), and 21 responded on 3 days (13%). Fifty-six percent of our participants identified as male, and 44% identified as female. The average age was 46.50 years ($SD = 9.50$), and the average tenure in the current job was 12.05 years ($SD = 8.69$). The most common industries represented were education and arts (13.5%), business-related services (11.0%), information technology and scientific services (9.8%), and health care (8.0%).

Measures

Unless otherwise indicated, question stems focused on the workday (e.g., “How does the following apply to your work today? Today”). We applied a Likert-type answering format, where response anchors ranged from 1 (*not at all*) to 5 (*completely*). Scales developed in English were translated into French by the first author and translated back to English by the fourth author based on procedures detailed by Brislin (1970). The rare divergences were resolved by consensus. Following best practices of reliability estimation (Geldhof et al., 2014), we report the within-person Cronbach α for our multi-item measures.

End-of-Day Cognitive Performance

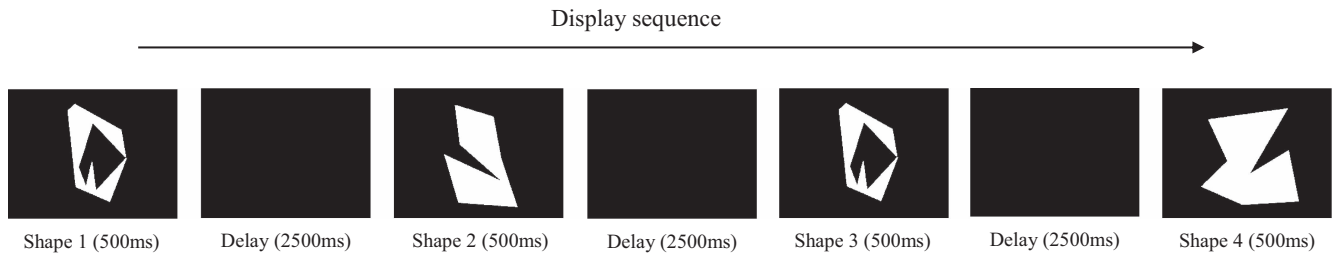
We administered a cognitive task extensively used by researchers in a lab setting to examine cognitive performance: the n -back task (Jaeggi, Buschkuhl, et al., 2010; Jaeggi, Studer-Luethi, et al., 2010). Consistent with prior studies (Jaeggi, Studer-Luethi, et al., 2010), we presented participants with a series of abstract shapes and asked them to indicate, by pressing a key, if the shape being presented matches the one presented “ n ” trials before. We chose to use $n = 2$ for this task (i.e., that the current shape matched the one presented two trials before) in order to simulate a high-demand task. According to prior research (Sliwinski et al., 2006; Verhaeghen & Basak, 2005), in the 1-back task, the item remains in a state of immediate accessibility, and recall is cognitively effortless. In contrast, in the 2-back task, recall is cognitively effortful because of the high cognitive demand involved in switching the attentional focus from one item to another. [Figure 1](#) provides an illustration of the n -back task we used.

We displayed the shapes for 500 ms, and there was a 2,500 ms delay before the presentation of the next shape, such that participants had 3,000 ms to press the key. Consistent with the literature (Allom & Mullan, 2014; Jaeggi, Studer-Luethi, et al., 2010), we measured cognitive performance in the n -back task using the following formula⁴:

² Data from the project “The impact of resistance to efforts to bring about change on change agents’ wellbeing and cognitive functioning”/no institutional review board (IRB) protocol number allocated.

³ Based on Welch’s t tests, there were no significant differences in age, $t(432) = -0.849, p = .396$; gender, $t(432) = -1.214, p = .226$; and tenure, $t(432) = 0.684, p = .495$, between participants who completed only the baseline survey and our final sample. Based on person-aggregated data, there were no differences in task proactivity, $t(211.10) = 0.443, p = .658$; end-of-day cognitive performance, $t(211.45) = -0.890, p = .375$; and task performance, $t(275) = -0.420, p = .675$, between participants who were not included in the analysis because they only responded on 1 or 2 days and our final sample.

⁴ While some lab studies consider response time as an additional measure of cognitive performance, we chose not to use it in our ambulatory assessment as it may be impacted by differences in participants’ device system capabilities and functioning at measurement time.

Figure 1*Illustration of the n-Back Task (n = 2)*

Note. In the *n*-back task, we presented participants with a series of abstract shapes and asked them to indicate, by pressing a key, if the shape being presented matches the one presented “*n*” trials before. We chose to use *n* = 2 for this task. For example, here, when presented with Shape 3, participants should press the key because this shape matches Shape 1 presented two shapes before. When presented with Shape 4, participants should not press any key because this shape does not match Shape 2 presented two shapes before.

$$\text{Cognitive Performance} = \frac{\text{Total Hits} - \text{Total False Alarms}}{\text{Number of Total Blocks}}, \quad (1)$$

where “hits” means that the participant correctly identified a shape and “false alarms” means that participants incorrectly identified the shape as being the one previously presented.

To measure end-of-day cognitive performance, we used a short version of the *n*-back task to enhance compliance and reduce the burden placed on participants (Beal, 2015; Hektner et al., 2007; Ohly et al., 2010). This version we used was tested and validated by past research (Jaeggi, Studer-Luethi, et al., 2010; Sliwinski et al., 2006; Stawski et al., 2006). In the daily survey, participants viewed three “blocks,” or sets of shapes. Each block contained 20 experimental trials, six of which contained “hits” and 14 of which were nontarget shapes. Prior to each daily measure, we included practice trials, not counting toward the task score, to remind participants of the task and its requirements (Jaeggi, Buschkuhl, et al., 2010).

Task Proactivity

We assessed task proactivity with Griffin et al.’s (2007) scale of three items, adapting it to the needs of our daily diary study design. A sample item is “Today, I initiated better ways of doing my core tasks.” This scale has already been validated for a daily diary study design (Ma et al., 2020). Based on Geldhof et al. (2014), the within-person coefficient α was .86.

Control Variables

At the within-person level, we controlled for task performance, defined as behaviors aimed at completing one’s prescribed core task (Williams & Anderson, 1991). Controlling for task performance aims to establish that the relationship with cognitive performance is specific to task proactivity and does not apply to performing core tasks in a routine way. We assessed task performance using Williams and Anderson’s (1991) measure. This scale has already been validated for a daily diary study design (Halbesleben & Wheeler, 2011). We adapted the wording to the time frame of the present study. Additionally, to reduce completion burden on participants (Beal, 2015; Hektner et al., 2007; Ohly et al., 2010), we reduced the number of items used in the original Williams and Anderson’s (1991) seven-item scale to four items. A sample item is:

“Today, I adequately completed assigned duties.” The within-person coefficient α was .89.

Analysis Strategy

Because our data have two levels (day-level data nested within individuals), we conducted multilevel regression analysis with fixed slopes to test our hypothesis using Mplus Version 8.8 (Muthén & Muthén, 2017). We centered all within-person predictors (“group-mean” centering) for each individual across days (D. A. Hofmann & Gavin, 1998). This strategy eliminates between-person variance in predictors so that results show within-person associations.

Results

Table 1 presents the means, standard deviations, intraclass correlations (ICCs), and correlations. Before testing our hypothesis, we checked for the level of intraindividual variability. The level of within-person variance for our dependent variable (end-of-day cognitive performance) was 29%. The level of within-person variance for our predictor and control variable was 51% and 41%, respectively. Such levels of within-person variance confirm the adequacy of a multilevel analysis strategy.

We first assessed the discriminant validity of task proactivity and task performance by running a multilevel confirmatory factor analysis using Mplus Version 8.7 (Muthén & Muthén, 2017). We modeled our factors at both the between- and within-person levels (Preacher et al., 2010) to account for and separate between- and within-person variance. We used maximum-likelihood estimation with robust standard errors.

We estimated a two-factor model, treating task proactivity and task performance as separate constructs. This model provided a good fit to the data, $\chi^2(27) = 55.301, p < .001$; comparative fit index (CFI) = .989; Tucker–Lewis index (TLI) = .983; root-mean-square error of approximation (RMSEA) = .039; standardized root-mean-square residual (SRMR) within = .032; SRMR between = .043; $n = 163, k = 701$. We then compared this two-factor multilevel measurement model with the more parsimonious one-factor model, $\chi^2(29) = 1316.472, p < .001$; CFI = .511; TLI = .292; RMSEA = .252; SRMR within = .208; SRMR between = .290; $n = 163, k = 701$. The latter had a poorer model fit in comparison to the two-factor model, $\Delta\chi^2(2) = 1705.929, p < .001$.

Table 1*Means, Standard Deviations, ICCs, and Correlations (Study 1)*

Variable	<i>M</i> (B)	<i>SD</i> (B)	<i>M</i> (W)	<i>SD</i> (W)	1 – ICC	1	2	3	4	5
Within-person level										
1. End-of-day cognitive performance	2.41	2.01	2.43	2.26	0.29	—	–.21***	–.12**		
2. Task proactivity	2.17	0.91	2.15	1.16	0.51	–.25**	—	.13***		
3. Task performance	4.19	0.66	4.19	0.80	0.41	–.18*	.11	—		
Between-person level										
4. Gender ^a	0.56	0.50				.14	–.06	–.04	—	
5. Age	46.50	9.50				–.13	.00	–.02	.19*	—

Note. Means and standard deviations at the between level (B) are based on person-aggregated data ($n = 163$ participants). Means and standard deviations at the within-person level (W) are based on day-level data for within-person-level variables ($k = 701$ days). Correlations below the diagonal are based on person-aggregated data ($n = 163$ participants). Correlations above the diagonal are based on day-level data for within-person-level variables ($k = 701$ days). ICC = intraclass correlation.

^aGender: 0 = female, 1 = male.

* $p < .05$. ** $p < .01$. *** $p < .001$ (two-tailed).

Table 2 presents the results of the multilevel regression analyses. In Model 1, we regressed end-of-day cognitive performance on task proactivity as a within-person-level predictor. Task proactivity was negatively associated with end-of-day cognitive performance ($\gamma = -0.16$, $SE = 0.06$, $p = .010$). Therefore, our hypothesis was supported.

To verify that the relationship with end-of-day cognitive performance is specific to proactively improving core tasks rather than merely performing core tasks, we controlled for task performance in Model 2. The results showed that task performance was not significantly associated with end-of-day cognitive performance ($\gamma = 0.10$, $SE = 0.09$, $p = .261$). At the same time, task proactivity remained negatively associated with end-of-day cognitive performance ($\gamma = -0.17$, $SE = 0.06$, $p = .006$).

Discussion

We hypothesized that task proactivity is negatively associated with end-of-day cognitive performance. Study 1 supported our hypothesis, and results established the negative link between task proactivity and end-of-day cognitive performance, controlling for task performance. However, all daily measures were obtained at the same point in time, which does not allow us to establish a temporal

ordering of our variables. While cognitive performance was measured at the time implied in our theorizing (i.e., at the end of the day), task proactivity at work was measured only retrospectively. Therefore, in Study 2, we collected data from participants several times a day, such that task proactivity was assessed during working hours, whereas cognitive performance was still collected at the end of the day. Furthermore, in order to make the analyses more robust against reverse causality, we also measured levels of cognitive performance in the early morning, that is, prior to assessing task proactivity. Thus, we conducted Study 2 to replicate the findings of Study 1 and to overcome its limitations.

Study 2

Participants, Design, and Procedure

We followed the same participant recruitment procedure as in Study 1. We applied a longitudinal design within each day, which included three daily measurement points per day over seven workdays. We assessed beginning-of-day cognitive performance in the morning (surveys active between 5 a.m. and 10 a.m. with answers around 7:40 a.m. on average), task proactivity and task performance around noon (surveys active between 11 a.m. and 2 p.m. with answers around 12:10 p.m. on average), and end-of-day cognitive performance in the evening (surveys active between 8 p.m. and midnight with answers around 9:00 p.m. on average). This time separation was chosen to reduce common method bias (Podsakoff et al., 2003) and enhance confidence in the temporal ordering of our variables while also allowing sufficient time for the effects of task proactivity to emerge. Participants received a monetary compensation of up to €33.30, depending on the number of days and surveys they participated in. As for Study 1, the procedures for this study were approved by the ESSEC Research Ethics Committee.⁵

A total of 315 participants fulfilled the same screening criteria as in Study 1 and responded to a baseline survey including demographic characteristics and a cognitive task (45% response rate). The daily surveys included cognitive tasks as well as daily measures of our variables. We invited all participants in the baseline

Table 2*Results of Multilevel Path Analysis With End-of-Day Cognitive Performance as Dependent Variable (Study 1)*

Variable	Model 1		Model 2	
	γ	<i>SE</i>	γ	<i>SE</i>
Intercept	2.411***	(0.16)	2.411***	(0.16)
Within level				
Task performance			0.100	(0.09)
Task proactivity	–0.156**	(0.06)	–0.166**	(0.06)
AIC	5049.09		5050.17	
BIC	5076.41		5082.04	
ssBIC	5057.36		5059.81	
Change in ssBIC	–2.68		2.46	

Note. $n = 163$ participants; $k = 701$ days. Changes in ssBIC compare Model 1 with an unconstrained model and Model 2 with Model 1. *SE* = standard error; AIC = Akaike information criterion; BIC = Bayesian information criterion; ssBIC = sample size-adjusted Bayesian information criterion.

** $p < .01$. *** $p < .001$ (two-tailed).

⁵ Data from the project “An integrative perspective on the well-being consequences of proactive behavior at work”/no IRB protocol number allocated.

survey for the surveys of Days 1–5, always excluding those who failed attention check items from later surveys following best practices for online data collection (Cheung et al., 2017). To obtain data from at least 3 days for each participant, on Day 6, we invited back only participants who responded on at least 1 day; and on Day 7, only those who responded on at least 2 days were invited.

Excluding participants who failed attention check items, our final sample⁶ consisted of a total of 471 days collected from 93 participants who completed the evening survey, which assessed the dependent variable, for at least 3 days, out of which 58 provided data for 5–7 workdays (62%), 20 for 4 days (22%), and 15 for 3 days (16%). Fifty-nine percent of our participants identified as male, 41% identified as female. The average age was 43.58 years ($SD = 8.66$), and the average tenure in the current job was 12.18 years ($SD = 8.84$). The most common industries represented were business-related services (21.5%), education and arts (12.9%), manufacturing and engineering (11.8%), commercial trades (10.7%), and IT and scientific services (8.6%).

Measures

Unless mentioned otherwise, we applied the same measures as in Study 1.

Cognitive Performance (Evening)

We collected end-of-day cognitive performance at the end of the day.

Task Proactivity (Noon)

We assessed individual task proactivity around noon. The within-person coefficient α was .87.

Control Variables

We controlled for daily beginning-of-day cognitive performance (morning). Once again, we controlled for task performance, which was assessed at the same time as our predictor, task proactivity (noon). The within-person coefficient α of task performance was .83.

Analysis Strategy

We applied the same analysis strategy used in Study 1, adding our new control variable (beginning-of-day cognitive performance) at the within-person level and group-mean centering it for each individual across days. In contrast to Study 1, where a single measurement point meant that if a participant did not complete the survey, we had no data to include in our analyses, in Study 2, we had multiple measurement points. As a result, a participant could have completed only some of the daily surveys. By not including incomplete participation days in our analysis, we run the risk of losing participation days and valuable data even if partial. Thus, to deal with missing values, we estimated our models applying the full information maximum likelihood (FIML) estimation approach (Newman, 2014). Instead of imputing missing values, FIML is an estimation method that minimizes missing data bias by analyzing the incomplete data set and estimating model parameters and standard errors using likelihood functions that maximize observed data's probability (Enders, 2001; Newman, 2014). Research attributes

many benefits to FIML estimation: providing unbiased parameter estimates and accurate standard errors, maximizing statistical power, and yielding computational efficiency (Enders, 2001; Enders & Bandalos, 2001; Newman, 2014).

Little's (1988) missing completely at random test revealed that values for beginning-of-day cognitive performance and task proactivity in our final sample were missing completely at random, $\chi^2(2) = 2.904$, $p = .234$. Under these conditions, according to Newman (2014), the use of FIML is thus possible, and FIML estimation is unbiased with accurate estimated standard errors.

Results

Table 3 presents the means, standard deviations, ICCs, and correlations. The level of within-person variance for our dependent variable (end-of-day cognitive performance) was 36%. The level of within-person variance for our predictor and control variables (task proactivity, task performance, and beginning-of-day cognitive performance) was between 35% and 45%. Such levels of within-person variance confirm the adequacy of a multilevel analysis strategy.

We assessed the discriminant validity of task proactivity and task performance by running a multilevel confirmatory factor analysis using Mplus and following the same procedure as in Study 1. We estimated a two-factor model, treating task proactivity and task performance as separate constructs. This model provided a good fit to the data, $\chi^2(27) = 27.760$, $p = .42$; CFI = .999; TLI = .999; RMSEA = .008; SRMR within = .027; SRMR between = .031; $n = 89$, $k = 407$. We then compared this two-factor multilevel measurement model with a more parsimonious one-factor model, $\chi^2(28) = 798.534$, $p < .001$; CFI = .377; TLI = .065; RMSEA = .260; SRMR within = .227; SRMR between = .287; $n = 89$, $k = 407$. The latter had a poorer model fit in comparison to the two-factor model, $\Delta\chi^2(1) = 333.962$, $p < .001$.

Table 4 presents the results of the multilevel regression analyses. In Model 1, task proactivity was negatively associated with end-of-day cognitive performance ($\gamma = -0.24$, $SE = 0.10$, $p = .022$). Our hypothesis was again supported.

In Model 2, we controlled for task performance and found that it was not significantly associated with end-of-day cognitive performance ($\gamma = -0.06$, $SE = 0.18$, $p = .761$). Once again, task proactivity remained negatively associated with end-of-day cognitive performance ($\gamma = -0.24$, $SE = 0.10$, $p = .023$).

We then introduced beginning-of-day cognitive performance as a predictor in Model 3. This measure was positively associated with end-of-day cognitive performance ($\gamma = 0.23$, $SE = 0.07$, $p = .001$). Importantly, task proactivity remained negatively associated with end-of-day cognitive performance ($\gamma = -0.20$, $SE = 0.10$, $p = .044$).

⁶ Welch's t tests showed no significant differences in age, $t(192.22) = 1.256$, $p = .211$; gender, $t(313) = -0.535$, $p = .593$; and tenure, $t(313) = -0.939$, $p = .349$, between participants who completed only the baseline survey and our final sample. Based on person-aggregated data, there were no differences in beginning-of-day cognitive performance, $t(107) = -0.979$, $p = .330$; task proactivity, $t(126) = 0.762$, $p = .448$; end-of-day cognitive performance, $t(150) = -0.541$, $p = .589$; task performance, $t(126) = -0.533$, $p = .595$; conflict with coworkers, $t(73.59) = 1.902$, $p = .061$; workload, $t(101.34) = -1.331$, $p = .186$; and multitasking, $t(109.99) = -0.093$, $p = .926$, between participants who were not included in the analysis because they only responded on 1 or 2 days and our final sample.

Table 3
Means, Standard Deviations, ICCs, and Correlations (Study 2)

Variable	M (B)	SD (B)	M (W)	SD (W)	1 - ICC	1	2	3	4	5	6	7	8	9
Within-person level (main analysis)														
1. End-of-day cognitive performance	2.87	1.86	2.92	2.16	0.36	—	-.02	.05	.69***	-.12*	.12*	.03		
2. Task proactivity	1.61	0.77	1.96	1.05	0.45	-.03	—	-.09	-.01	.12*	.15**	.23***		
3. Task performance	4.24	0.68	4.38	0.65	0.35	.09	-.04	—	.09	-.21***	.15**	.04		
4. Beginning-of-day cognitive performance	3.12	1.65	3.24	1.96	0.44	.88***	-.02	.11	—	-.09	.04	-.10		
Within-person level (supplemental analysis)														
5. Conflict with coworkers	1.13	0.32	1.15	0.49	0.64	-.12	.18	-.18	-.15	—	.02	.10*		
6. Workload	3.36	0.82	3.38	1.01	0.45	.18	.35***	.19	.11	.05	—	.46***		
7. Multitasking	2.84	1.11	2.86	1.26	0.31	.08	.30**	.07	-.14	.13	.50***	—		
Between-person level														
8. Gender ^a	0.59	0.49				.01	.17	-.16	-.03	-.06	-.12	.13	—	
9. Age	43.58	8.66				-.13	-.00	.13	-.17	-.15	.19	-.01	-.05	—

Note. Means and standard deviations at the between-person level (B) are based on person-aggregated data ($n = 85$ participants at the beginning of day, 89 at noon, and 93 at the end of day). Means and standard deviations at the within-person level (W) are based on day-level data for within-person-level variables ($k = 391$ data points at the beginning of day, 407 at noon, and 471 at the end of day). Correlations below the diagonal are based on person-aggregated data ($n = 85$ participants at the beginning of day, 89 at noon, and 93 at the end of day). Correlations above the diagonal are based on day-level data for within-person-level variables ($k = 391$ data points at the beginning of day, 407 at noon, and 471 at the end of day). ICC = intraclass correlation.

^aGender: 0 = female, 1 = male.
* $p < .05$. ** $p < .01$. *** $p < .001$ (two-tailed).

Discussion

Study 2 replicated our findings from Study 1 that task proactivity is negatively associated with end-of-day cognitive performance, controlling for task performance. Going further, Study 2 allowed us to establish the temporal ordering of our two focal variables and to assess the constructs at the time we expected them to unfold (task proactivity during work hours, cognitive performance after work hours). Additionally, another limitation of Study 1 was that individuals may have experienced low end-of-day cognitive performance because they may have started the day with low levels of cognitive performance in the first place rather than because they engaged in task proactivity. Our results showed that task proactivity predicted end-of-day cognitive performance above and beyond beginning-of-day cognitive performance, bringing further support to our hypothesis.

Supplemental Analysis

We conducted two supplemental analyses to determine whether (a) stressors may be responsible for the relationship between task proactivity and end-of-day cognitive performance and (b) whether time (and thus learning effects) may have an impact on the relationship between task proactivity and cognitive performance. First, our model builds on the assumption that engaging in task proactivity entails elevated levels of cognitive demands that foster mental fatigue and that this mental fatigue will be reflected in poorer cognitive performance. However, task proactivity may also give rise to stressors, which might alternatively be responsible for the decline in cognitive performance (e.g., Luethi et al., 2009; Sliwinski et al., 2006). Specifically, task proactivity could potentially cause social stressors (Bolino et al., 2010; Spsychala & Sonnentag, 2011), such as conflict with colleagues. Individuals engaging in task proactivity may also have to deal with additional task components (Fay & Hüttges, 2017), which means an increase in workload and multitasking. Therefore, in order to rule out that the identified link between task proactivity and cognitive performance is based on other processes, such as the experience of stressors and additional work demands, we seek to demonstrate that the effect of task proactivity holds even when we control for these variables.

We assessed conflict with coworkers, workload, and multitasking using one item, each adapted from Zhang et al. (2014). We collected these measures in the evening. We used them as additional control variables by extending Model 3, which already included controls for task performance and beginning-of-day cognitive performance. The results of Model 4 show that task proactivity remained negatively associated with end-of-day cognitive performance ($\gamma_{\text{proactivity}} = -0.20$, $SE = 0.10$, $p = .047$) while controlling for conflict with coworkers, workload, and multitasking ($\gamma_{\text{conflict}} = -0.09$, $SE = 0.28$, $p = .739$; $\gamma_{\text{workload}} = 0.05$, $SE = 0.11$, $p = .659$; $\gamma_{\text{multitasking}} = -0.06$, $SE = 0.12$, $p = .579$).

Results from our first supplemental analysis show that the effect of task proactivity on end-of-day cognitive performance cannot be accounted for by alternative explanations such as conflict with coworkers, workload, and multitasking. Controlling for these variables brings further confidence in our assumption that the effect is indeed based on the cognitive processes task proactivity entails.

Second, cognitive performance in a task may be subject to learning effects as time goes by. After repeated practice in a specific

Table 4*Results of Multilevel Path Analysis With End-of-Day Cognitive Performance as Dependent Variable (Study 2)*

Variable	Model 1		Model 2		Model 3		Model 4	
	γ	SE	γ	SE	γ	SE	γ	SE
Intercept	2.880***	(0.19)	2.880***	(0.19)	2.882***	(0.19)	2.882***	(0.19)
Within level								
Task performance			−0.055	(0.18)	−0.058	(0.19)	−0.058	(0.19)
Beginning-of-day cognitive performance					0.232**	(0.07)	0.231**	(0.07)
Task proactivity	−0.238*	(0.10)	−0.236*	(0.10)	−0.202*	(0.10)	−0.202*	(0.10)
Conflict with coworkers							−0.095	(0.28)
Workload							0.051	(0.11)
Multitasking							−0.064	(0.12)
AIC	6312.25		6314.13		6299.97		6305.05	
BIC	6353.80		6359.83		6349.82		6367.38	
ssBIC	6322.06		6324.92		6311.74		6319.77	
Change in ssBIC	−1.97		2.86		−13.18		8.03	

Note. $n = 85$ – 93 participants; $k = 391$ – 471 days. Change in ssBIC compares each model with the previous one, except for Model 1 that we compare with an unconstrained model. SE = standard error; AIC = Akaike information criterion; BIC = Bayesian information criterion; ssBIC = sample size-adjusted Bayesian information criterion.

* $p < .05$. ** $p < .01$. *** $p < .001$ (two-tailed).

cognitive task, participants are likely to reach a plateau where the impact of learning is maximized and performance levels stabilize (Yamashita et al., 2015). At this point, performance of a cognitive task that is now well-rehearsed and therefore no longer requires mental effort is unlikely to be affected by preceding cognitive demands. A well-learned task would thus most likely not detect the impact of task proactivity on cognitive performance. Thus, following Gabriel et al. (2019), we examined the relationship between time (expressed as the number of days of participation in our study) and cognitive performance levels. We focused on beginning-of-day cognitive performance as it represents baseline cognitive performance before any work-related behavior participants have engaged in comes into play. Figure 2 presents the evolution of mean beginning-of-day cognitive performance levels by participation day. Fitting a polynomial trendline shows increasing levels up to Day 3, after which the trendline flattens.

We conducted Wilcoxon signed-ranks tests to assess differences in beginning-of-day cognitive performance levels across participation

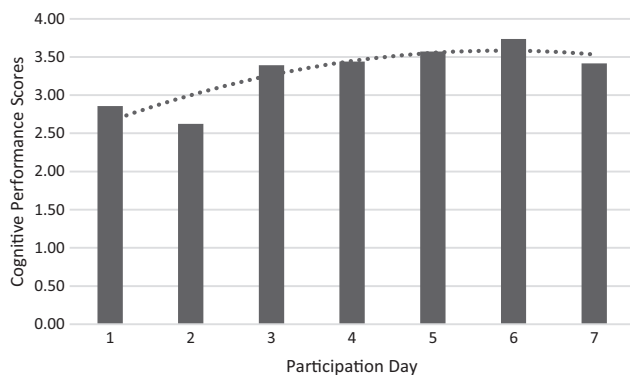
days, each time comparing cognitive performance in two consecutive participation days for the same participants. Cognitive performance in Day 1 (mean rank = 21.04) was significantly different ($Z = -2.67$, $p = .008$) from that of Day 2 (mean rank = 22.37). Cognitive performance in Day 2 (mean rank = 26.67) was also significantly different ($Z = -3.878$, $p < .001$) from that of Day 3 (mean rank = 35.43). Cognitive performance in the following pairs of participation days was not significantly different, with the exception of Day 5 and Day 6.

Given these observations, we dichotomized the participation day variable into 0 (Day ≤ 3 : ongoing learning) and 1 (Day ≥ 4 : performance plateau) and used it as a moderator to the relationship between task proactivity and end-of-day cognitive performance. The results showed that the interaction between participation day and task proactivity is significant ($\gamma_{\text{Participation Day} \times \text{Proactivity}} = 0.38$, $SE = 0.19$, $p = .041$). Further, a simple slopes analysis showed that during the first 3 days (ongoing learning), engaging in proactivity has a significant negative effect on end-of-day performance (effect = -0.28 , $SE = 0.14$, $p = .047$). As participants move on to 4 days of participation and more (performance plateau), this effect turns nonsignificant (effect = 0.07 , $SE = 0.11$, $p = .502$).

Results from our second supplemental analysis show that task proactivity is related to end-of-day cognitive performance as long as the cognitive task (we used to measure cognitive performance) requires mental effort. Once the task has been sufficiently rehearsed and learned, task proactivity and end-of-day cognitive performance are no longer related. Together, Studies 1 and 2 thus support our hypothesis that task proactivity is negatively associated with end-of-day cognitive performance. Yet in these daily diary studies, we were not able to assess the proposed underlying theoretical mechanisms, that is, that task proactivity requires greater mental effort and involves a deviation from routines, or to establish whether or not ego-depletion processes account for our findings. We thus conducted two experiments to test these effects.⁷

Figure 2

Evolution of Mean Beginning-of-Day Cognitive Performance Levels by Participation Day



Note. The bar chart is based on $n = 93$ participants and $k = 391$ days.

⁷ We are grateful to two anonymous reviewers for suggesting this.

Study 3

Participants, Design, and Procedure

In Study 3, we manipulated task proactivity in a scenario experiment in order to (a) provide support for the proposed direction of causality, (b) examine the proposed mechanisms of increased mental effort and reduced routineness, and (c) rule out ego depletion as a competing theoretical mechanism. The procedures for this study were approved by the ESSEC Research Ethics Committee.⁸ This study was preregistered (<https://aspredicte.d.org/zu6sx.pdf>), and its materials can be found in [Supplemental Material A](#).

We investigated whether the mental simulation of task proactivity results in a higher level of experienced mental effort and a lower level of perceived task routineness compared to the mental simulation of a core task in a within-subjects experiment. Our design included two conditions: (a) a routine task condition in which participants were asked to reflect on a core task that they have to routinely complete in their job and describe it in detail and (b) a task proactivity condition in which participants were asked to reflect on a core task in their job, suggest ways in which it could be done more efficiently, and describe in detail how they would implement this change. Participants were allocated to both conditions in a random order. After each experimental manipulation, participants reported their perceived level of task proactivity, experienced mental effort, routineness, ego depletion, and subjective fatigue.⁹

We recruited, via Prolific Academic, 434 participants based in the United Kingdom who were currently employed and required the survey to be completed on a computer or laptop to ensure that participants could easily complete the writing tasks. Six participants failed an instructed attention check item and were thus excluded from the analyses. In line with our preregistered exclusion criteria, we further excluded participants who spent less than 3 min on the experimental manipulation, resulting in a final sample of 318,¹⁰ out of which 188 were randomly allocated to the task proactivity condition first. Participants were, on average, 40.0 years old. Forty-three percent of participants identified as male, 55.7% identified as female, and the remaining participants identified as neither or preferred not to disclose their gender. Participants worked in a range of industries, such as business-related services (20.1%), education and arts (13.5%), and IT and scientific services (11.9%).

Measures

Unless otherwise indicated, question stems focused on the experimental manipulation through the writing tasks (e.g., “To what extent does the following apply to what you described?”). We applied a Likert-type answering format, where response anchors ranged from 1 (*not at all*) to 5 (*to a great extent*).

Task Proactivity

We assessed task proactivity with [Griffin et al.’s \(2007\)](#) scale of three items. A sample item is “(In what I described) I initiated better ways of doing my core tasks” ($\alpha_{\text{routine task condition}} = .94$; $\alpha_{\text{task proactivity condition}} = .89$).

Mental Effort

We measured mental effort with [Hart and Staveland’s \(1988\)](#) National Aeronautics and Space Administration Task Load Index (NASA-TLX) subscale for mental demand, adapted for the needs of our study to obtain three items. We used the question stem “Think about the moment when you wrote down your core task” for the routine task condition and “Think about the moment when you wrote down the changes you could implement” for the task proactivity condition. A sample item is “How much mental activity was required of you in terms of thinking hard, reflecting on pros and cons?” on a scale of 1 (*low*) to 10 (*high*; $\alpha_{\text{routine task condition}} = .91$; $\alpha_{\text{task proactivity condition}} = .89$). We also measured mental effort using [Zijlstra’s \(1995\)](#) single-item Rating Scale Mental Effort (RSME). We applied the question stem “How hard did you have to work mentally in order to provide the information required for the previous description?” on a scale of 0 (*absolutely no effort*) to 150 going through 110 (*extreme effort*), as translated into English and used by [Alimohammadi et al. \(2019\)](#).

Routineness

We assessed routineness using [Chung and Jackson’s \(2013\)](#) task routineness measure. We adapted the wording to the experimental manipulation of the present study. Additionally, to reduce completion burden on participants ([Beal, 2015](#); [Hektner et al., 2007](#); [Ohly et al., 2010](#)), we reduced the number of items from 4 to 3. A sample item is “The way of accomplishing my task will be very routine” ($\alpha_{\text{routine task condition}} = .77$; $\alpha_{\text{task proactivity condition}} = .58$).

Ego Depletion

We assessed ego depletion with five items used by [Lanaj et al. \(2014\)](#) adapted from a scale developed by [Twenge et al. \(2004\)](#) and published by [Christian and Ellis \(2011\)](#). The question stem was “To what extent does the following apply to you right now?” A sample item is “(Right now,) it takes a lot of effort for me to concentrate on something” ($\alpha_{\text{routine task condition}} = .89$; $\alpha_{\text{task proactivity condition}} = .89$).

Subjective Fatigue

We assessed subjective fatigue using [Watson and Clark’s \(1994\)](#) four-item fatigue subscale of the expanded form of the Positive and Negative Affect Schedule. The question stem was, “To what extent does the following apply to you right now?” A sample item is “(Right now, I feel) tired” ($\alpha_{\text{routine task condition}} = .93$; $\alpha_{\text{task proactivity condition}} = .92$).

⁸ Data from the project “Task proactivity, routines, and mental effort”/IRB protocol number: 2023-16.

⁹ We are grateful to an anonymous reviewer for proposing the inclusion of this additional competing mechanism.

¹⁰ There are no substantive changes in our findings when this exclusion criterion is not applied. The repeated measures ANOVA shows that the effect of the experimental conditions remains significant on task proactivity, $F(1, 432) = 201.80, p < .001$; experienced mental effort, $F(1, 432) = 44.93, p < .001$ for the NASA-TLX subscale measure and $F(1, 432) = 35.05, p < .001$ for the RSME measure; and routineness, $F(1, 432) = 103.83, p < .001$. The repeated measures ANOVAs show that the effect of the experimental conditions remains nonsignificant on ego depletion, $F(1, 432) = 1.27, p = .260$, and subjective fatigue, $F(1, 432) = 0.08, p = .771$.

Table 5*Descriptive Statistics of Variables by Experimental Condition (Studies 3 and 4)*

Experimental condition	Mental effort (NASA-TLX subscale)		Mental effort (RSME)		Routineness		Subjective fatigue		Ego depletion		Self-control demands		Self-control effort		Self-control motivation	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Study 3																
Task proactivity	5.49	2.12	71.60	30.45	3.13	0.84	1.95	0.96	1.88	0.84						
Routine task	4.49	2.33	60.53	31.26	3.65	0.90	1.94	0.95	1.88	0.81						
Study 4																
Task proactivity	5.40	1.95	58.80	26.67	3.18	0.80	2.15	1.11	2.02	0.99	2.22	0.77	2.28	0.98	3.22	1.01
Routine task	4.93	2.13	51.37	26.16	3.82	0.86	2.16	1.02	2.05	0.95	2.10	0.75	2.30	0.96	3.20	0.94

Note. Study 3: $N = 318$; Study 4: $N = 319$. NASA-TLX = National Aeronautics and Space Administration Task Load Index; RSME = Rating Scale Mental Effort.

Analysis Strategy

We performed repeated-measures ANOVAs to evaluate the effect of our experimental conditions (routine task condition vs. task proactivity condition) on task proactivity (manipulation check), experienced mental effort and routineness (proposed mechanisms), and ego depletion and fatigue (competing mechanisms). Table 5 shows the descriptive statistics across experimental conditions. Overall sample statistics and correlations are shown in Supplemental Material B.

Results

The effect of the experimental conditions on task proactivity was significant, $F(1, 316) = 149.93, p < .001$, partial $\eta^2 = .322$, providing support for our manipulation of task proactivity. Participants reported higher levels of task proactivity ($M = 3.73, SD = 0.95$) after the task proactivity condition in comparison to the routine task condition ($M = 2.68, SD = 1.23$). Repeated-measures ANOVAs showed significant within-subject differences between the task proactivity condition and the routine task condition in terms of mental effort, $F(1, 316) = 68.01, p < .001$, partial $\eta^2 = .177$ for the NASA-TLX subscale measure and $F(1, 316) = 50.29, p < .001$, partial $\eta^2 = .137$ for the RSME measure, and routineness, $F(1, 316) = 86.76, p < .001$, partial $\eta^2 = .215$. In the task proactivity condition, participants reported higher levels of experienced mental effort (NASA-TLX subscale measure: $M = 5.49, SD = 2.12$; RSME measure: $M = 71.60, SD = 30.45$) and lower levels of routineness ($M = 3.13, SD = 0.84$) compared to the routine task condition (NASA-TLX subscale measure: $M = 4.49, SD = 2.33$; RSME measure: $M = 60.53, SD = 31.26$; routineness: $M = 3.65, SD = 0.90$). These results lend support to our proposed mechanisms.

In contrast, repeated-measures ANOVAs showed no significant within-subject differences between the task proactivity condition and the routine task condition in ego depletion, $F(1, 316) = 0.147, p = .701$, partial $\eta^2 = .000$, or subjective fatigue, $F(1, 316) = 0.190, p = .663$, partial $\eta^2 = .001$, failing to support competing mechanisms.

Study 4

In Study 4, we explored the competing theoretical mechanism of increased self-control demands and resulting ego depletion in more

detail. It is plausible that task proactivity could pose greater self-control demands by requiring individuals to override their impulses, resist distraction, and overcome resistance (Diestel & Schmidt, 2011). Task proactivity could thus deplete their self-regulatory resources, resulting in reduced self-control motivation (Kotabe & Hofmann, 2015) and thus in reduced self-control effort (Wehrt et al., 2020).

Participants, Design, and Procedure

To explore this competing theoretical mechanism, we investigated the effects of task proactivity on participants' perceived self-control demands, self-control motivation, self-control effort, and level of ego depletion (self-control resource depletion), as well as on mental effort and routineness, in a between-subjects experiment. The procedures for this study were approved by the ESSEC Research Ethics Committee.¹¹ Task proactivity was manipulated with the same procedure as in Study 3. We recruited 663 participants via Prolific Academic. We recruited participants based in the United Kingdom who were currently employed and required the survey to be completed on a computer or laptop to ensure that participants could easily complete the writing task. Seven participants failed an instructed attention check item and were thus excluded from the analyses. We further excluded participants who spent less than 3 min on the experimental manipulation, in line with the preregistered exclusion criteria of Study 3, resulting in a final sample of 319.¹² Participants were, on average, 41.4 years old. Forty-seven percent of participants identified as male, 51.6% identified as female, and the remaining participants identified as neither or preferred not to disclose their gender. Participants worked in a range of industries, such as business-related services (19.4%), education and arts (17.6%), and health care (12.9%).

¹¹ Data from the project "Task proactivity and ego depletion"/IRB protocol number: 2023-17.

¹² There are no substantive changes in our findings when these exclusion criteria are not applied. The MANOVA with the four self-control demand-related variables remains nonsignificant, $F(4, 651) = 1.48, p = .21$, partial $\eta^2 = .009$, and the MANOVA for mental effort and routineness remains significant, $F(3, 652) = 30.60, p < .001$, partial $\eta^2 = .123$.

Measures

As in Study 3, unless otherwise indicated, question stems focused on the experimental manipulation through the writing tasks, and response anchors ranged from 1 (*not at all*) to 5 (*to a great extent*).

Task proactivity ($\alpha = .92$), mental effort (NASA-TLX subscale: $\alpha = .85$; the single item RSME), routineness ($\alpha = .69$), subjective fatigue ($\alpha = .94$), and ego depletion ($\alpha = .93$) were assessed with the same measures as in Study 3.

Self-Control Demands

The self-control demands posed by simulating task proactivity (task proactivity condition) or simulating completing a routine task (routine task condition) were assessed with the 15-item measure by Schmidt and Diestel (2015), adapted to focus on our experimental tasks. Example items are as follows: “I was not allowed to become impatient” (impulse control), “The task was such that I really need to force myself to get it done.” (overcoming resistance), and “The task required me to resist distraction” (resisting distractions). Cronbach’s α was .89. Following Schmidt and Diestel (2015), the three aspects of self-control demands were collapsed into a single measure.

Self-Control Effort

Participants’ experienced self-control effort was measured with nine items by Wehrt et al. (2020). A sample item is “(Right now, I am making a lot of effort) to not let myself be distracted.” Cronbach’s α was .94.

Self-Control Motivation

Self-control motivation was assessed with nine items by Wehrt et al. (2020). A sample item is “(Right now, I am motivated) not to become impatient.” Cronbach’s α was .93.

Results

Table 5 shows the descriptive statistics across experimental conditions. Overall sample statistics and correlations are shown in Supplemental Material C. As in Study 3, participants in the task proactivity condition reported higher levels of task proactivity ($M = 4.08$, $SD = 0.86$) compared to the routine task condition, $M = 2.70$, $SD = 1.23$; $t(317) = -11.54$, $p < .001$, providing support for our manipulation of task proactivity. A multivariate analysis of variance (MANOVA) with the four self-control demand-related variables showed no significant differences between the task proactivity condition and the routine task condition, $F(4, 314) = 0.64$, $p = .66$, partial $\eta^2 = .008$. The two conditions did not differ in self-control demands, $F(1, 317) = 1.77$, $p = .18$, partial $\eta^2 = .006$; self-control motivation, $F(1, 317) = 0.07$, $p = .80$, partial $\eta^2 = .000$; self-control effort, $F(1, 317) = 0.01$, $p = .91$, partial $\eta^2 = .000$; or ego depletion, $F(1, 317) = 0.09$, $p = .77$, partial $\eta^2 = .000$. In contrast, a MANOVA of the two measures of mental effort and routineness showed significant differences between conditions, $F(3, 315) = 16.62$, $p < .001$, partial $\eta^2 = .137$. Participants in the task proactivity condition reported significantly greater mental effort, three-item NASA-TLX subscale measure: $F(1, 317) = 4.16$, $p = .04$, partial $\eta^2 = .013$; RSME: $F(1, 317) = 6.311$, $p = .012$, partial $\eta^2 = .020$, and significantly lower routineness, $F(1, 317) = 47.30$, $p < .001$, partial $\eta^2 = .130$. As in Study 3, there were no significant differences in

subjective fatigue between the task proactivity condition and the routine task condition, $t(317) = -0.08$, $p = .94$.

General Discussion

Task proactivity requires individuals to expend effort in order to improve the way they accomplish their core tasks (Griffin et al., 2007), which may entail cognitive costs (Bolino et al., 2010). We argued that task proactivity involves deviation from routines and elevated levels of mental effort, which may in turn result in mental fatigue. In two daily diary studies, we found that engaging in task proactivity was associated with poorer end-of-day cognitive performance, even when controlling for task performance and beginning-of-day cognitive performance. In two experiments, we then demonstrated that task proactivity resulted in decreased routineness and led to increased mental effort.

Theoretical Implications

We contribute to the literature in several ways. First, we investigate the cognitively demanding nature of proactivity and its relationship with cognitive functioning. Prior literature has hinted at the cost of proactivity for individuals (Belschak et al., 2010; Bolino et al., 2010), with empirical studies focusing on affective and social mechanisms and outcomes (e.g., Cangiano et al., 2019; Fay & Hüttges, 2017; Sun et al., 2021) and conceptual work hinting at processes of depletion (e.g., Bateman, 2017; Bolino et al., 2010). Our research builds on and extends the literature on consequences of proactivity. The findings of our daily diary studies indicate that, even when considering alternative mechanisms (conflict, workload, and multitasking), task proactivity had a negative association with cognitive performance. While it may well be that finding more efficient ways of doing one’s job reduces cognitive demands in the long run, in its immediate aftermath, individuals’ cognitive performance was reduced. On days on which individuals engage in task proactivity, individuals seem to experience higher cognitive demands that foster mental fatigue, leaving limited room for efficient cognitive processing at the end of the day. We suggested that, by engaging in task proactivity, individuals break from prescribed ways of doing and leave task routines, which entail complex cognitive processes (Kanfer & Ackerman, 1989; Norman & Bobrow, 1975; Ohly et al., 2006, 2017). This may explain our findings regarding the differential relationship of task proactivity and task performance with end-of-day cognitive performance. Whereas task performance is likely to be less cognitively demanding because core tasks are typically performed following a routine, task proactivity may be more cognitively demanding because developing and enacting a different way of performing core tasks involves complex cognitive processes. Our experimental studies further support the argument that task proactivity is associated with increased mental effort and reduced routineness. This is relevant to understand the potential consequences of other types of change-oriented work behaviors. Because diverging from routines may not be exclusive to engaging in task proactivity, our findings suggest that cognitive costs may result from other behaviors that change the way tasks are performed (e.g., innovative behavior).

We sought to rule out that our findings could be accounted for by increased self-control demands associated with task proactivity and by resulting reduced self-control motivation and -effort and

increased self-control resource depletion (ego depletion). Despite controversy surrounding the ego depletion effect and its replicability (Carter et al., 2015; Hagger et al., 2016), it seemed imperative to differentiate our proposed mechanism of increased cognitive demands from this alternative theoretical explanation. In our experiments, task proactivity was not associated with ego depletion or self-control demand-related variables, providing support for our proposed mechanism of increased cognitive costs. These findings contribute to our understanding of resource-intensive behaviors at work more generally. In research drawing on resource depletion theories, it is common that it remains unclear exactly what resources are being depleted (Lian et al., 2017). In their review, Lian et al. (2017) concluded that “[a]lthough we do not yet know exactly what the [depleted] resources are, we have a good idea about what the resources are not. In particular, the resources do not appear to be cognitive resources” (p. 15). Yet despite this, scholars often suggest increased cognitive demands as a mechanism that explains depletion, and in the proactivity literature, authors have argued that proactivity may be associated with both cognitive and self-control demands. Our goal was thus to differentiate these different types of demands.

In addition, in Study 4, we sought to also capture changes in willingness to exert self-control. This motivational process provides an alternative explanation for ego-depletion effects (Inzlicht et al., 2014). We found no differences in self-control motivation between the task proactivity condition and the routine task condition. This again seems to suggest that processes other than self-control are at play. By disentangling cognitive demands and self-control-related processes and by drawing on theories of mental fatigue rather than ego depletion, we thus provide an alternative framework for the study of resource-intensive behaviors at work, such as proactivity.

Second, the relationship between task proactivity during the workday and end-of-day cognitive performance may imply that the effects of task proactivity-related cognitive demands persist over the course of the day. Prior studies involving lab experiments have demonstrated that cognitive performance immediately following cognitively demanding tasks declines (Lavric et al., 2000; Norman & Bobrow, 1975). Furthermore, this decline in performance has been theorized as rather immediate and temporary in nature (Baddeley, 2003; Barrouillet et al., 2007; Wickens, 1991). Our findings seem to suggest that the effects of cognitive demands resulting from task proactivity persist over the workday and result in the observed negative relationship with cognitive performance at the end of the day (even when controlling for cognitive performance at the beginning of the day). Our data also show that end-of-day cognitive performance is on average lower than beginning-of-day cognitive performance, yet the decline of cognitive performance over the day covaries with level of task proactivity exhibited on this day. These results extend the perspective that cognitive performance may suffer not only temporarily with fast recovery because the results suggest that the effects of cognitive demands may persist over the course of the day, resulting in mental fatigue (Danziger et al., 2011; Linder et al., 2014). Going further, by using a non-domain-specific measure of cognitive performance (performance in the *n*-back task), our results lend preliminary support to the idea that, beyond persisting after working hours, the impact of cognitively demanding activities may carry over to other sometimes unrelated tasks involving cognitive performance.

Further, our study investigates cognitive performance in a novel way by combining an objective measure with a diary study. The

benefits of this design are twofold. First, instead of relying merely on self-reports, we administered the “*n*-back task,” a cognitive task used to examine cognitive performance (Jaeggi, Buschkuhl, et al., 2010; Jaeggi, Studer-Luethi, et al., 2010). This objective measure allows us to alleviate common method bias (Podsakoff et al., 2003). It allows a direct probing of cognitive performance away from individual biases and perceptions. Second, the daily diary study design allowed us to administer the *n*-back task outside a lab setting. Collecting timely data using a daily diary study in a natural setting allows participants to remain embedded in their natural life contexts (Bolger & Laurenceau, 2013; Ohly et al., 2010). Studying cognitive performance in this novel way, combining an objective measure with a diary study design, allows for realistic conditions and assessment of our outcome variable.

Practical Implications

From a practical standpoint, our findings suggest that higher levels of task proactivity can be associated with impaired cognitive functioning (Clarkson et al., 2011; Engle, 2002). Attending to this issue is paramount in today’s world, where organizations are increasingly pressuring individuals to engage in proactive behavior to achieve organizational expectations (Bolino et al., 2010). Our findings suggest the possibility that on days when individuals have shown high levels of task proactivity, they might perform comparatively poorly toward the end of the workday in job activities that imply cognitive processing. Knowing that cognitive processes (e.g., analyzing information, solving problems, learning) intervene in a wide range of cognitive tasks individuals call upon on a daily basis (Baddeley, 1983, 2003; Engle, 2002; Ma et al., 2020), organizations should be particularly attentive to the cognitive state of their employees. Indeed, in extreme cases, a deterioration in cognitive performance might lead to mistakes or even fatal errors (e.g., a doctor making the wrong call on a medicine that leads to life-threatening consequences for a patient). Encouraging employees to engage in cognitively demanding task proactivity should go hand in hand with fostering everyone’s awareness about potential costs. Managers can also help employees gain awareness about potential resulting mental fatigue and organize their workdays around short breaks, for example, as research has hinted at the fatigue-alleviating role of breaks (Danziger et al., 2011).

Limitations and Future Directions

Our study is subject to limitations. Based on previous theory and empirical evidence, we hypothesized that task proactivity would be related to end-of-day cognitive performance because of the cognitive demands it implies. The finding that cognitive performance was lower on days when individuals engaged in task proactivity provides support for this argument, as do the results of our experimental studies, which show that individuals reported expending greater mental effort when simulating task proactivity.¹³ Future research may decompose proactive behavior into processes or phases (following, e.g., Bindl et al., 2012; Frese & Fay, 2001;

¹³ In supplementary experiments with a student sample in the laboratory and an online panel, we did not find an effect of our task proactivity manipulation on *n*-back performance. However, exploratory post hoc analyses showed a negative relationship between mental effort and cognitive performance in the laboratory and suggest that an experimentally induced effect of task proactivity on cognitive performance may be observable under some circumstances (see [Supplemental Materials F and G](#)).

Sonnentag & Starzyk, 2015) in order to understand the implications of each for cognitive performance. In fact, it may be that certain processes bring about higher cognitive demands than others and may thus have a stronger impact on cognitive performance.

In the daily diary studies, we investigated the relationship of task proactivity with end-of-day cognitive performance on a daily basis, which does not allow us to draw conclusions about longer term effects of task proactivity. Indeed, despite an initial negative impact on cognitive performance, finding better and more efficient ways of doing one's job may reduce the cognitive demands it poses as time goes by. A longitudinal study covering weeks or months may assess the long-term impact of task proactivity on end-of-day cognitive performance.

Task proactivity involves finding new ways of completing one's task through cognitively demanding processes such as information processing, analysis, reasoning, and learning from trial and error. Finding new and/or more efficient ways of doing one's job is inherent in a range of different approaches through which individuals contribute to organizations, such as individual innovation (Scott & Bruce, 1994; Wu et al., 2014) or taking charge (Morrison & Phelps, 1999). Like task proactivity, these behaviors are likely to involve the cognitive demands associated with deviating from established ways of working through demanding cognitive processes. Further research is thus needed to explore whether and to what extent our effect generalizes to other behaviors.

We sought to establish that the relationship of task proactivity with cognitive performance was likely to be due to increased mental effort and a taxing deviation from routines rather than increased self-control demands and resulting ego depletion, and our findings largely support this argument. However, it is important to note that other forms of proactive behavior may involve greater self-control demands than task proactivity. For example, presenting an idea for an improved process in the team may involve suppressing emotional responses to colleagues' skepticism (impulse control). Further studies are needed to disentangle cognitive demands and self-control demands resulting from different proactive behaviors and identify the specific resources involved in these processes.

Future research may also investigate additional boundary conditions of the relationship between task proactivity and end-of-day cognitive performance. Individual differences or job conditions may accentuate or buffer the taxing effects of task proactivity. For example, it may be that in an unsupportive environment, such as one characterized by a lack of psychological safety (Edmondson, 1999), implementing improvements is associated with greater interpersonal risks. Anticipating others' reactions may place an additional burden on the individual. Similarly, it may be that particularly conscientious individuals pay greater attention to details and consider all possible eventualities when engaging in task proactivity, which potentially increases the associated mental effort. It is also plausible that situational constraints both may trigger proactive behavior (Fay & Sonnentag, 2002) and cause stress, which impacts cognitive performance (Gärtner et al., 2014; Schoofs et al., 2008). Further research is needed to disentangle these dynamic relationships.

Our design is also subject to limitations. In our field studies, the predictor—task proactivity—and the control variables rely on self-reported measures. Although self-assessment is the most direct way to capture individuals' subjective state, some of our data may be subject to common method bias. In order to avoid and minimize this

risk (Podsakoff et al., 2003), we implemented different strategies, including assuring confidentiality to alleviate potential social desirability, using attention check items, and assessing the dependent variable, cognitive performance, through an objective measurement (the *n*-back task). Further, the choice of a daily diary study design helps reduce retrospection and alleviate memory biases (Beal, 2015; Bolger et al., 2003; Ohly et al., 2010; Robinson & Clore, 2002). This minimizes the period between the occurrence of the event of interest and its reporting to a few hours. Future studies may consider collecting reports on task proactivity from colleagues and supervisors. However, given that it may be difficult for supervisors or colleagues to reliably observe task proactivity, there clearly is value in self-reports of task proactivity. It is also important to note that the reliability of the measure of task routineness in Studies 3 and 4 was fairly low, suggesting that future studies using a more reliable measure are needed.

Together, our experimental studies provide evidence of the proposed direction of causality. However, it is also plausible that cognitive demands in turn affect individuals' capacity to engage in proactive behavior. To explore this possibility, we conducted an experiment in which we first manipulated the cognitive demands faced by participants by having them complete either a 1-back task or a more demanding 2-back task. We then assessed their subsequent propensity for proactive behavior through three items capturing task proactivity from a well-established situational judgment test (Bledow & Frese, 2009). There were no differences in task proactivity between the high and low cognitive demand conditions (see Supplemental Material D for the detailed procedure and results). Together with Studies 3 and 4, this provides some support for the direction of causality we proposed. Future research is nevertheless needed to explore the possibility that individuals are less likely to engage in task proactivity having faced higher cognitive demands.

Conclusion

To date, prior literature has only hinted at the cost of proactive behavior on cognitive performance without explicitly exploring such a phenomenon. Our studies aimed to investigate the cognitively demanding nature of proactivity and its impact on cognitive functioning. We provided empirical evidence that high levels of individual task proactivity are associated with low levels of end-of-day cognitive performance. We argue that this effect is due to elevated levels of cognitive demands fostering mental fatigue. Our findings highlight the cognitively intensive nature of proactive behavior and suggest that, in its immediate aftermath, individuals incur a cognitive cost that persists over the course of the day.

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Received October 3, 2022

Revision received February 23, 2024

Accepted February 25, 2024 ■

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