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Using mental contrasting to promote flow experiences at work: A just-in-time adaptive intervention

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ABSTRACT

Using repeated measurements in everyday life, we assessed whether a smartphone-based just-in-time adaptive intervention prompting use of metacognitive strategies enhances flow at work. Assuming that setting clear goals and disengaging from unattainable or undesirable goals enables individuals to engage in tasks aligned with their skills, we expected that mentally contrasting positive outcomes of a wish with an inner obstacle to the realization of this wish increases flow compared to a simple goal-setting strategy. We reminded participants (N = 59 knowledge workers) either adaptively or statically to use mental contrasting or the control goal-setting strategy. Repeated strategy use increased the likelihood of experiencing flow regardless of the specific strategy employed. However, results show that flow increases more over time when applying mental contrasting than the control strategy. Our findings fail to confirm the superiority of the prompt using an adaptive decision rule for when the person receives support compared to the static prompt. We discuss the necessity of assessing extended periods to examine differences between adaptive and static support in terms of habit formation and intervention fatigue. Our study contributes to the development of smartphone-based, adaptive interventions for knowledge workers which enable them to autonomously increase their flow in everyday life.

1. Introduction

As reflected by the current discourse around the phenomenon of quiet quitting (Atalay & Dağıstan, 2023; Harter, 2022; Newport, 2022), only 23 % of employees worldwide were engaged in their work in 2022 (Gallup, 2022). This lack of work engagement negatively impacts performance and well-being, and increases turnover rates (Mazzetti et al., 2021). To counteract this trend, popular media outlets and scientific articles promote the idea of cultivating intrinsic motivation by allowing individuals to select tasks aligned with their skills (Fishbach & Woolley, 2022; Paulise, 2022). Given this demand to support employee engagement, the concept of flow which was originally coined by Csikszentmihalyi (1975) has regained popularity. Flow is an intrinsically motivating state of mind that emerges when a person's skills align perfectly with the demands of their task, in that the person feels neither bored nor overburdened (Nakamura & Csikszentmihalyi, 2012). In this state, individuals experience complete immersion in their current task which directly relates to beneficial work-related outcomes such as increases in performance, energy levels, or creativity (Demerouti et al., 2012; Engeser & Rheinberg, 2008; Zubair & Kamal, 2015).

Despite these flow-evoked benefits, interventions for promoting flow at work are still scarce (Bartholomeyczik et al., 2023). This scarcity is largely due to the strong variability of flow. Individuals differ not only in their general proneness to experiencing flow, but flow state also depends on the task, situation, and time (Ceja & Navarro, 2011; Fullagar & Kelloway, 2009; Nielsen & Cleal, 2010; Tse et al., 2021). Hence, interventions that cannot only adapt to interindividual differences (i.e. support individuals who hardly experience flow), but also to within-person changes (i.e. support individuals who work on tasks that hardly elicit flow in them) are needed. This is possible by using just-in-time adaptive interventions (JITAIs). JITAIs build on an "intervention design that employs adaptation to operationalize the provision of just-in-time support, namely to provide the right type (or amount) of support, at the right time, while eliminating support provision that is not beneficial" (Nahum-Shani et al., 2018, p. 450). Hence, to develop a JITAI that promotes flow at work, it is necessary to decide which specific type of intervention should be provided adaptively to the person. Then, it is possible to evaluate whether giving this intervention type adaptively

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is more beneficial for promoting flow than providing non-adaptive assistance. In the following sections, we will examine both of these aspects with regard to theoretical literature and prior empirical studies. Then we will explain the present research in more depth highlighting how it provides the first empirical investigation of how to promote flow adaptively in everyday knowledge work. In this article, we specifically focus on knowledge work which involves "finding, creating, packaging, and applying knowledge" independent of specific work domain (Kelloway & Barling, 2000, p. 301). Knowledge work is typically complex and cognitively demanding, thereby ensuring that the major precondition of flow, namely working on a challenging task (Engeser & Rheinberg, 2008), is met.

1.1. Use of mental contrasting as the intervention type

In a recent theoretical overview of flow interventions in the workplace (Bartholomeyczik et al., 2023), the authors propose selecting the intervention type based on its specific aim, target, and executor. The authors recommend focusing initially on establishing the necessary flow preconditions (skill-demand-balance, clear goals, and feedback; Nakamura & Csikszentmihalyi, 2012), as these factors are pivotal for the emergence of flow. Contextual factors dictate the constitution of these preconditions to some extent (e.g. when a job comes with certain tasks, or a manager assigns specific goals). However, individuals can also contribute to their fulfillment. For that, the intervention type should directly target and be executable by the individual. Thereby, employees can self-initiatively promote their flow regardless of organizational context (Bartholomeyczik et al., 2023).

In line with such an individual-rather than context-focused approach, a recent study by Weintraub et al. (2021) found that nudging workers to set goals according to the SMART acronym (commonly interpreted as specific, measurable, attainable, relevant, and time-bound goals; Rubin, 2002; Swann et al., 2022) increased daily flow at work. This association between goal-setting and flow (e.g. also see Oertig et al., 2014; Schweickle et al., 2017) arises because choosing goals increases goal commitment by enhancing perceived goal importance (Locke & Latham, 2002). Since goal importance is a known moderator for the emergence of flow, choice of goals might then also facilitate flow (Engeser & Rheinberg, 2008). Most importantly, setting clear goals helps people structure their tasks. Thereby, they feel more productive and as if their skills align with the task, a core precondition of flow (Bakker & van Woerkom, 2017; Csikszentmihalyi et al., 2014).

However, assuming that the structuring effect of goal-setting promotes flow presumes that the goals persist until they are fulfilled or deserted. But goals may turn out to be non-achievable or they may become undesirable. This would require rethinking the goal and the respective plan to pursue it. Acknowledging these processes of goal disengagement (Oettingen & Gollwitzer, 2022) is one special feature of mental contrasting (MC). MC is a stepwise procedure that lets people identify an important wish or goal and then mentally contrast the imagined best outcome of this wish with the anticipated main obstacle (Oettingen, 2000; Oettingen et al., 2010). By vividly imagining the wished-for future, people will find the direction to act, and by subsequently imagining the obstacle standing in the way of attaining the wished-for future, people will recognize that they must go the hard way of overcoming the obstacle. Thus, they will increase their efforts to overcome the obstacle on the way to wish fulfilment. However, people may also recognize that an obstacle is impossible to surmount or not worth overcoming. Then, they will either adjust the wish, postpone it to a more opportune time, or actively let go of wish fulfillment (Oettingen et al., 2001; Riddell et al., 2022; Sevincer & Oettingen, 2013). This will allow them to save time and resources, especially when managing multiple goals (Riddell et al., 2023). Thereby, goal adjustment has been found to be associated with increases in positive affect (Riddell et al., 2022).

Interestingly, the conscious procedure of MC leads to behavior changes via nonconscious cognitive processes (e.g., associative links between wish and outcome), motivation (e.g., energy measured by systolic blood pressure), and responses to feedback (e.g., increased receptivity to critical feedback). By these processes, mental contrasting produces behavior change outside of conscious awareness (e.g., Kappes & Oettingen, 2014; summary by Oettingen & Sevincer, 2018). In sum, via these nonconscious processes, MC facilitates goal pursuit when the obstacle is surmountable. However, if the obstacle is too costly to overcome or insurmountable, mental contrasting encourages people to actively let go of their wish (Oettingen, 2000; Oettingen et al., 2001). Finally, finding an internal and controllable obstacle will increase the chances of engagement rather than disengagement (Oettingen, 2012).

Individuals can learn MC in a short amount of time independent of the content of the wish. This quick learning prepares them to apply MC as a metacognitive strategy in various contexts with different wishes or goals (Oettingen et al., 2015). Earlier research indicates that MC can successfully be applied by different target groups (e.g., students or nurses) and influence both behavior (e.g., attenuate procrastination; Oettingen et al., 2015) and emotions (e.g., decrease regret and disappointment; Krott & Oettingen, 2018).

The mental contrasting of the best outcome and the main obstacle distinguishes MC from goal-setting strategies (e.g. setting SMART goals). While these strategies emphasize setting attainable goals, they do not explicitly focus on obstacles or juxtapose them with the outcomes. This could add value to MC for its impact on flow in knowledge work for two reasons. First, deciding which wishes are worth pursuing based on the contrast between anticipated outcomes and obstacles lets individuals a priori choose tasks that align with their skills. Overall, the person then engages in balanced tasks more often which enhances the likelihood of experiencing flow. Second, deciding which goals to pursue and which to let go increases perceived autonomy. Earlier research indicates that autonomous choice of tasks can compensate for nonoptimal compositions of skills and demands, thereby allowing similarly high flow as would be expected for an optimal balance (Bartholomeyczik et al., 2022; de Sampaio Barros et al., 2018). Hence, especially at work where tasks are often extrinsically motivated (Peifer & Wolters, 2021), MC may increase perceived autonomy, thereby facilitating the emergence of flow.

1.2. Promoting flow adaptively

Since flow at work does not evolve similarly across individuals and situations (Engeser & Baumann, 2016), interventions should not be provided independent of these factors. Yet, in the aforementioned intervention study using SMART goal-setting to foster flow at work, Weintraub et al. (2021) nudged all participants to apply the strategy every morning. This approach of using a static intervention, i.e. providing the intervention independent of the individual's state, comes with relevant disadvantages. For example, earlier research suggests that static interventions might cause intervention fatigue, "a state of emotional or cognitive weariness associated with intervention engagement" (Nahum-Shani et al., 2018, p. 450). Intervention fatigue arises when the demand of adhering to the intervention, alongside contextual demands during application, exceeds individual capacities such as affective and cognitive resources (Heckman et al., 2015). This is especially relevant in modern digital workplaces, where individuals frequently face a high number of demands competing for their attention (Marsh et al., 2022). In addition, research from the domain of eHealth suggests that users quickly stop using mobile applications if these do not adapt to their individual states (Christensen & Mackinnon, 2006; Eysenbach, 2005). This so-called law of attrition (Eysenbach, 2005) argues for adapting the support provision to the user. Thereby, it is possible to avoid providing support in situations when people simply lack the capacity to adhere to the intervention (Nahum-Shani et al., 2018).

Apart from these outcome-unspecific disadvantages, static interventions bear additional downsides for the aim of promoting flow. First, repeatedly reminding people to apply the intervention reduces their autonomy. As discussed before, however, autonomy is a relevant determinant of flow (Bartholomeyczik et al., 2022; de Sampaio Barros et al., 2018). Also, while individuals may generally benefit from increased flow at work, on some days they may experience flow often enough to not need additional support. On these days, the intervention may lose its effect or, at worst, cause negative side effects. For example, too frequent or long states of flow might exploit individuals' attentional capacities causing exhaustion (Zimanyi & Schüler, 2021). Since static interventions do not consider whether a person already experiences flow frequently, they run the risk of overstimulating flow.

JITAIs could overcome these general and flow-specific limitations of static interventions by providing flow-supporting strategies only when needed. In the context of increasingly digitized workplaces, leveraging smartphone-based assistance could be a particularly appealing resource to realize this objective in real-world scenarios. For that, JITAIs include a decision rule that specifies a decision point (i.e. the time of decision) at which the value of a tailoring variable is used as a determinant for which intervention option is offered (Nahum-Shani et al., 2018). To provide flow support only when needed, the tailoring variable needs to contain information about flow state during everyday work tasks. A suitable method for gaining such insights in an unobtrusive way is ambulatory assessment. Ambulatory assessment allows to measure everyday experiences while individuals go about their day (Trull & Ebner-Priemer, 2014). Hence, digital self-reports on flow obtained through ambulatory assessment (which are also commonly used in non-interventional flow research, Moneta, 2021) may serve as the tailoring variable in an adaptive decision rule. Based on this information, flow-supporting strategies can be provided as needed to prevent intervention fatigue or overstimulation of flow.

1.3. The present research

Based on the aforementioned considerations with regard to the intervention type and adaptivity, we cover two major research questions in the present research. First, we aim for evaluating the flow-promoting effect of MC in knowledge work. Assuming that setting clear goals and disengaging from unattainable or undesirable goals enables individuals to autonomously engage in tasks with a higher likelihood of inducing flow, we expect that MC increases flow compared to a simple goal-setting strategy (Hypothesis 1). The second aim of our study is to evaluate whether a smartphone-based JITAI excels a static intervention with regard to its effect on flow at work. More specifically, we expect that the use of an adaptive decision rule for when the person receives support is more helpful for increasing flow compared to a static, non-adaptive prompt (Hypothesis 2).[1]

Our study contributes to flow research at the intersection of psychology, information systems, and human-computer interaction in at least two major ways. First, by assessing the potential of the metacognitive strategy MC with regard to promoting flow in knowledge work, we provide a simple, time- and cost-efficient approach which can help knowledge workers autonomously influence their flow. Since smartphones are portable and ubiquitous in everyday work, we specifically provide a smartphone-based intervention, accelerating the potential of our approach for use in an applied context. As a second contribution, we evaluate the usefulness of an adaptive compared to a static decision rule for promoting flow at work. Identifying an appropriate tailoring variable and its respective decisive values for when to provide support as part of an adaptive decision rule is essential for building a comprehensive flow-adaptive system. This system could function as the underlying architecture for providing flow-promoting JITAIs in everyday life independent of specific intervention type.

[1] Both hypotheses were preregistered on June 12th, 2023 (https://osf.io/a42xr/?view_only=294dc6d663a54fc29f1a15cc6b0adece). Please note that the naming of the effects of interest was changed to enhance clarity.

2. Material and methods

2.1. Procedure and participants

The study took place in three waves[2] in July and August 2023. Each participant completed the study in two weeks, which started and finished with a session in the laboratory. In between these introductory and final sessions, we applied smartphone-based ambulatory assessment.

In the introductory session, after obtaining informed consent, we provided participants with a smartphone (Android system) with the pre-installed app movisensXS (version 1.5.23, Movisens GmbH, Karlsruhe, Germany, 2022). Alongside this, participants provided demographic data, completed a baseline measure of flow proneness, took part in a practice session for the intervention type (see SI 1A for full instructions), and received information for the next part of the study. The smartphone-based ambulatory assessment and application of the intervention type then took place over five consecutive workdays (Monday through Friday). After this part of the study, we instructed participants to return the smartphone to the lab, complete a follow-up measure of flow proneness, give feedback on the intervention type, and provide payment details. We determined compensation according to the local minimum wage and dependent on the amount of time devoted to answering the queries for self-reports in the ambulatory assessment part of the study (maximum 33 EUR[3]). We offered an extra incentive of 10 EUR if participants completed more than 80 % of the queries.

Based on power estimates from Monte Carlo simulation (Arend & Schäfer, 2019), we recruited $N = 59$ knowledge workers (26 females, $M_{age} = 23.1$, $SD_{age} = 3.1$) from a pool for experimental studies at a European technical university (i.e., with a focus on STEM fields). To guarantee that participants were sufficiently engaged in knowledge work, we required them to perform mental tasks such as preparing for an exam or writing code for at least 4 h per day during the study period of five days. Participants reported that they were engaged in work activities during 58.3 % of the observations ($SD = 14.2$ %). Given that the observed time period was 10.5 h per day, this was, on average, consistent with the required minimum of four working hours per day. The study received approval from the local data protection office and ethics committee on April 19th, 2023.

2.2. Ambulatory assessment procedure

Since we were interested in participants' flow state during their everyday work tasks, we used time-based random sampling, i.e. we queried participants eight times per day between 9 a.m. and 7.30 p.m. (regular local working hours recognizing the flexible working hours common to knowledge work) including questions about their current task (i.e. what they were doing right before the query), flow state, and skill-demand-balance with at least 30 min between two queries (see section 2.4 for the exact wording). We announced pending queries via an acoustic notification on the smartphone. They could be postponed for 10 min. Each day, there was an additional e-diary query at 7.30 p.m. (which participants could postpone for an hour) asking retrospectively about overall flow experience during the day (see section 2.4 for the exact wording).[4] In the remainder of this article, we will refer to these smartphone-based queries for self-reports about momentary or recent individual experiences as *e-diary* queries.

[2] We randomly distributed assignment of participants to the experimental conditions (see below) over all waves.

[3] Compensation was reduced to 20 EUR if participants answered less than 65 % of queries.

[4] This e-diary also included items on work performance and stress. As these measures were not relevant to the present research question, we do not report them in this article.

Over all five days, participants answered $N = 2178$ queries ($n = 1886$ e-diary queries during the day, $n = 244$ evening e-diary queries). The mean compliance rate was $M = 80.23$ % ($SD = 15.06$) across all queries with similar participation on all days.

2.3. Experimental manipulation

For evaluating our two research questions, we experimentally manipulated the intervention type (MC or a control goal-setting strategy), and the decision rule determining when participants received flow support (adaptive or static). Thereby, there were four conditions (MC-adaptive, MC-static, control-adaptive, control-static) to which we randomly assigned participants in the introductory session (based on a computer-generated random number sequence; $n = 15$ in all groups except for control-static with $n = 14$). In sum, all participants acquired a metacognitive strategy for application in everyday life while the type of strategy and the mechanism for prompting the use of the strategy differed depending on condition.

2.3.1. Intervention type

The introductory session included a practice session in which participants worked through written computer-based instructions for acquiring the intervention type (MC or a control goal-setting strategy). In all four conditions, we told participants that they would learn a mental strategy to increase their motivation and change their behavior at work. In the following, we will briefly describe the practice session. The exact wording of the instructions can be found in SI 1. The entire session was conducted on a desktop computer, with participants completing the written components in digital format.

In the MC condition, participants learned how to apply MC according to the sequence used in prior research (e.g. Oettingen et al., 2010, 2015). This sequence was as follows: First, the instructions guided participants to identify their most important, yet attainable wish with regard to their work tasks in the upcoming week. Then, they needed to write down the very best outcome of fulfilling this wish in a few words and to vividly imagine this outcome in their mind. After that, they wrote down their thoughts and images in a few sentences. Last, they needed to identify the most important inner obstacle that may hold them back from fulfilling the wish, for example an emotion, a belief, or an ingrained habit. Again, we promoted them to vividly imagine this obstacle and then to write down their thoughts in a couple of sentences. For example, one participant formulated the wish to finish their programming task. They expected to be proud of themselves when reaching this goal and recognized that doubting their own capabilities might arise as an obstacle (for examples of formulated wishes, outcomes and obstacles see also SI 2). Next, to strengthen the acquirement of MC as a metacognitive strategy (i.e. for applying it across contexts), participants completed a second written round of the aforementioned sequence, this time with regard to a wish about their interpersonal relations at work. Additionally, to illustrate that they can use MC just mentally (rather than writing down their thoughts and images) and with regard to shorter timeframes, we asked participants to complete a third round of MC. They should identify a wish relating to their work tasks in the next 24 h. Then, we provided step-by-step instructions for vivid imagination again, but no instructions to write down their thoughts. Last, we reminded them of the three steps of the strategy (wish, outcome, obstacle).

Since Weintraub et al. (2021) found that setting SMART goals promoted flow at work, we decided to use this goal-setting strategy as an active control condition for evaluating the effectiveness of MC. In the control condition, participants learned how to set SMART goals (i.e. specific, measurable, attainable, relevant, and time-bound goals) analogously to the MC condition, i.e. they completed three learning rounds in which they set goals with different content and timeframes (e.g., “hand in my math assignment until Friday next week”, “spend at least one evening with my friends next week”).

At the conclusion of the practice session with a total duration of no longer than 20 min, we asked participants to apply the acquired strategy with regard to their work every day in the upcoming week. We reminded them of this request during their everyday life depending on decision rule (see below).

2.3.2. Decision rule

In JITAIs, the decision rule operationalizes under which circumstances which intervention option is offered to the person (Nahum-Shani et al., 2018). In our study, independent of specific intervention type (MC versus control), there were two intervention options: either to prompt participants each day during the ambulatory assessment period of five days to apply the acquired intervention type, or to omit this prompt. If given, the prompt occurred in the morning (at 8.30 a.m., i.e., before the start of the e-diary queries to prevent participants from receiving the prompt to apply the intervention strategy at the same time as an e-diary query) and reminded participants of the respective components of their acquired strategy. This guidance was included in case participants had forgotten important details from the practice session. The prompt asked them to apply the strategy on a work-related concern of their choice that they wanted to address over the course of the day (see SI 1B for full instructions). Since intervention options of JITAIs should be applicable in a short amount of time during everyday life (Nahum-Shani et al., 2018), we did not require participants to write down their thoughts, so that the whole response to the prompt would not last longer than a couple of minutes. Indeed, the maximum time spent with answering a morning prompt was 4.5 min. If participants received a prompt, they could postpone it for half an hour. We asked them to answer it before they started working though.

We located the decision point for whether or not to present this prompt in the previous day. The decision rule also needs a decisive value, i.e., a cut-off in the tailoring variable that determines prompt presentation. Due to the risk of setting a suboptimal threshold when transforming continuous flow scores into categorical classifications (Abuhamdeh, 2020), we did not use the repeated reports of flow state over the day (reported on a continuous scale) as the tailoring variable. Instead, we used the retrospective categorical flow report provided once per day in the evening diary (see sections 2.2 and 2.4.1). Visual inspections implied that mean flow state during the day and the retrospective flow report in the evening diary corresponded with each other (Fig. 1). In line with that, Spearman-Brown corrected correlation between mean flow state (aggregated per day) and the respective daily

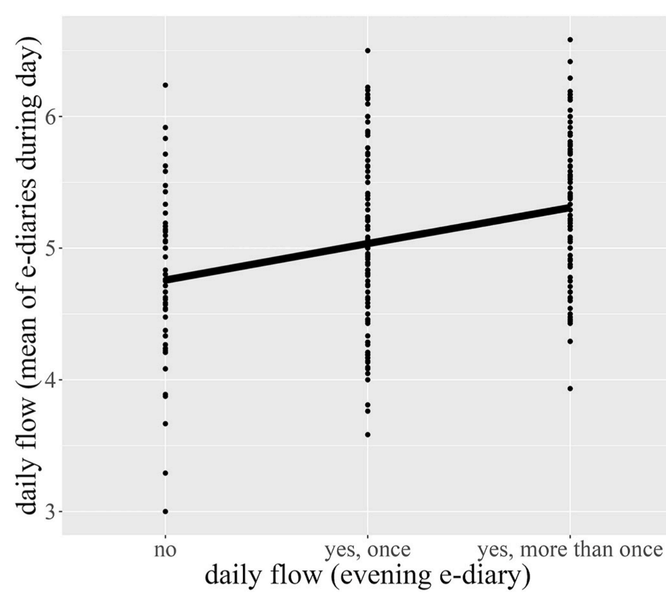

Fig. 1. Association between mean reported flow state during day and retrospective report of daily flow in the evening (thick line = mean association).

flow report was moderately positive (Cohen, 1992) within- (r = 0.47) and between-subjects (r = 0.54). This congruent estimation of daily flow by the two measures suggested that our tailoring variable provided a valid estimation of overall flow experience over the day for use in the adaptive decision rule.

The adaptive decision rule was as follows: If participants reported in the evening that they had experienced flow at most once during the day, they then received a prompt the morning after. If they had experienced flow more often than once, they did not receive a prompt in the next morning. By comparison, in the static condition, participants received the prompt every morning, i.e. independent of the answer to the tailoring variable (for an overview of decision rule in the adaptive compared to the static condition see Fig. 2). In sum, participants in all conditions received a prompt on Monday morning,[5] whereas the presentation of prompts on the other days, i.e. Tuesday to Friday depended on the condition.[6]

Participants in the static condition received M = 4.93 (SD = 0.26) prompts compared to M = 3.77 (SD = 1.36) prompts in the adaptive condition.[7] Statistical comparison of this difference with a Wilcoxon test (Shapiro-Wilk: $p < .05$) supported a significantly higher number of presented prompts in the adaptive compared to the static condition (W = 194, $p < .001$) indicating successful manipulation of decision rule. Since participants could ignore the prompt, the number of presented prompts could deviate from actual attendance to the prompts. On average, participants attended to 90.2 % of presented prompts. There was no statistically significant difference in attendance to presented prompts between the adaptive and the static condition (M_{static} = 90.5 %, M_{adaptive} = 89.8 %; p = .233).

2.4. Measures

Please refer to SI 9 for the exact wording of all items, respective answer scales, and sources.

2.4.1. Flow state

In the e-diaries during the day, we operationalized flow state with three items from the Flow Short Scale (Engeser & Rheinberg, 2008; Rheinberg, 2015), specifically the highest loading items for each of the two factors of the original scale (Rheinberg, Vollmeyer, & Engeser, 2003). A study by Bartholomeyczik et al. (2024) showed similarly good reliability and validity compared to the full scale. The reduced scale consists of three statements (items 6, 8, and 9 of the original scale, e.g., "I am totally absorbed in what I am doing"; Engeser & Rheinberg, 2008; Rheinberg, 2015).[8] Participants indicate their agreement on a seven-point Likert scale from "not at all" (1) to "very much" (7). We computed the mean across the three items with higher scores indicating higher flow state. Reliability (McDonald's Omega ω; Geldhof, 2014) was comparably high as in the validation study (within-subject: ω = 0.68, between-subjects: ω = 0.88).

In the evening e-diary, we additionally measured daily flow by using an ordinal item ("Have you experienced flow today?") with possible answers "No" (0), "Yes, once" (1), or "Yes, more than once" (2). We defined flow by showing different quotes to the participants in the introductory session (Moneta, 2012, p. 494; adapted from Csikszentmihalyi & Csikszentmihalyi, 1988): "My mind isn't wandering. I am totally involved in what I am doing, and I am not thinking of anything else. My body feels good … the world seems to be cut off from me … I am less aware of myself and my problems." "My concentration is like breathing … I never think of it … When I start, I really do shut out the world." "I am so involved in what I am doing … I don't see myself as separate from what I am doing."

2.4.2. Proneness to experiencing flow at work

To measure the general proneness to experiencing flow at work (i.e. independent of a particular event) as a baseline measure, we applied the full version of the Flow Short Scale (Engeser & Rheinberg, 2008; Rheinberg, 2015; ten items with a two-factorial structure as described above) in the introductory session (before the practice session for the intervention type). To capture potential changes after the intervention, we reapplied the measure when participants returned the smartphone to the lab. We asked participants to indicate their agreement with the statements regarding their work-related activities. Reliability (McDonald's Omega ω; Geldhof, 2014) was good within- (ω = 0.87) and between-subjects (ω = 0.76).

2.4.3. Task

In the e-diaries during the day, we asked participants to indicate their current task. We provided the question as a single-choice item with possible answers being work, obligations, leisure and other. To measure the flow precondition of a skill-demand-balance, we also let participants indicate the perceived degree of the task demands with regard to them personally from "too low" (1) to "too high" (7) (Engeser & Rheinberg, 2008) with "just right" (4) indicating optimal balance. Since earlier studies show that flow declines for deviations from this balance in either direction (Huskey et al., 2018; Keller et al., 2011; Tozman et al., 2015), we subtracted ratings of 4 from the answers and computed absolute values so that zero equals optimal balance and positive values indicate deviation from this balance in either direction.

2.4.4. Feedback about intervention type

At the end of the study, we applied a feedback questionnaire in which participants indicated their satisfaction with the intervention type ("I will use the strategy again") on a five-point Likert scale from "completely disagree" (0) to "completely agree" (4). They also reported if they had fulfilled all their formulated goals yet and if they used the strategy more than once on a single day (0 = no, 1 = yes).

2.5. Data analysis

We performed all data analyses in R Studio (Version 2023.06.2) with the packages multilevelTools (Wiley, 2020), misty (Yanagida, 2023), esmpack (Viechtbauer & Constantin, 2023), lme4 (Bates et al., 2023), and nlme (Pinheiro et al., 2023). For analyzing the ambulatory assessment data, we computed two-level linear mixed models to account for the nested data structure with repeated observations (level 1, n = 1886) within participants (level 2, N = 59). We used a stepwise approach to evaluate changes in flow state.[9] An overview of the structures of the following models is provided in Table 3 (see also SI 3 for additional model descriptions).

First, we computed the null model (random-intercept-only model) to

[5] Since there was no flow report from the preceding day available on the first study day (Monday), we presented a prompt to all participants on this day.

[6] If participants in the adaptive condition did not answer the tailoring variable in the evening, the prompt was shown by default in the next morning.

[7] Please note that there was a technical problem due to which two participants in the static condition did not receive a prompt on the last day of the observation period.

[8] The English version of the FKS (Engeser & Rheinberg, 2008) has been made publicly available for free use by Rheinberg (2015). In addition, the German scale (see Rheinberg, Vollmeyer & Engeser, 2019; https://doi.org/10.23668/psycharchives.4488) has been shared under a Creative Commons ShareAlike 4.0 License (https://creativecommons.org/licenses/by-sa/4.0/).

[9] Please note that the preregistration reports the full model including all predictors of interest (as in Model 5). We also planned to compute a generalized linear mixed model with flow frequency as the dependent variable. This analysis is excluded from this article due to concerns with the smaller sample size (only one observation of flow frequency per day instead of eight observations of flow state per day).

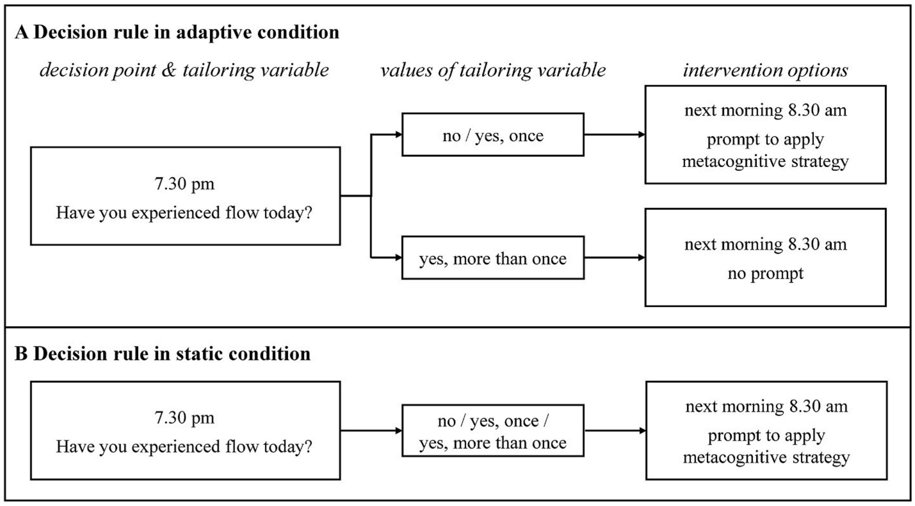

Fig. 2. Decision rule in comparison between conditions. In the adaptive condition (A), the morning prompt was presented to the participants depending on the answer to the tailoring variable "Have you experienced flow today?". In the static condition (B), the prompt was presented every morning independent of the answer to the tailoring variable.

Table 1
Descriptive statistics of variables assessed in e-diaries, at baseline and follow-up compared between conditions (A = adaptive, S = static, M = MC, C = control).

	M_{Total} (*SD*)	ICC	M_A (SD_A)	M_S (SD_S)	M_M (SD_M)	M_C (SD_C)
Flow state	5.05 (1.09)	0.18	5.04 (1.03)	5.06 (1.15)	5.02 (1.08)	5.08 (1.10)
Daily flow[a]	33.6 %	0.27	36.3 %	30.8 %	32.3 %	35.0 %
Skill-demand-balance	0.82 (0.83)	0.15	0.85 (0.83)	0.79 (0.84)	0.89 (0.83)	0.78 (0.83)
Flow proneness		–				
Baseline	4.05 (0.78)	–	4.23 (0.92)	3.87 (0.58)	4.00 (0.90)	4.11 (0.65)
Follow-up	4.33 (0.77)	–	4.39 (0.76)	4.26 (0.80)	4.20 (0.72)	4.47 (0.82)

Note. Flow state (rated on a seven-point Likert scale from one to seven) and skill-demand-balance (0 = balance; positive values indicate deviation from balance in either direction) were reported in the e-diaries during the day (Level 1, $n = 1886$) by the participants (Level 2, $N = 59$). Daily flow (single-choice item with possible answers "No", "Yes, once", or "Yes, more than once") was reported in the evening e-diary (Level 1, $n = 244$) by the participants (Level 2, $N = 59$). Flow proneness (rated on a seven-point Likert scale from one to seven) was reported at baseline ($N = 59$) and follow-up ($N = 58$). ICC = Intraclass correlation coefficient.
[a] Proportion of "Yes, more than once" responses reported instead of mean scores and standard deviations due to the single-choice variable.

evaluate within- and between-subject variability in flow state when none of the predictors of interest were included. We then entered the intervention type (0 = control, 1 = MC) and the decision rule (0 = static, 1 = adaptive) as predictors at Level 2, controlling for skill-demand-balance (person-mean centered, Level 1) and flow proneness at baseline (grand-mean centered, Level 2) (Model 1)[10]. Since the intervention type was prompted multiple times over the course of the ambulatory assessment period, we next added the effect of time (i.e., number of observations, Level 1) and two-way interactions between decision rule and time as well as intervention type and time to account for possible changes of effects over the week (Model 2). We centered the predictor time with zero being the last observation (i.e. the last e-diary query on Friday afternoon). This was due to the fact that all participants received a prompt on Monday morning independent of condition. Fisher's exact test did not indicate significant differences between the static and the adaptive condition in whether participants actually responded to this first prompt ($p = .707$). Thus, we could not interpret the effect of the decision rule for the first day (i.e. the first eight observations). Since participants had formulated the wishes or goals with regard to their work, we then added a fixed effect for the task type (0 = working, 1 = not working) to the model (Model 3). To further assess whether effects differed depending on flow proneness at baseline, we added this variable as a moderator for the effects of decision rule and intervention type as well as for the two-way interactions of these effects with time (Model 4). Lastly, we evaluated whether the effects of intervention type and decision rule on flow state interacted by adding a two-way interaction between rule and type to the model[11] (Model 5). All models included random effects for level 1 variables. We evaluated model fit with chi-square difference tests based on log-likelihood values comparing the nested models sequentially according to their increasing complexity (i.e., null model with model 1, model 1 with model 2, etc.).

3. Results

Descriptive statistics for the variables measured in e-diary queries, baseline and follow-up questionnaires are presented in Table 1 (for a corresponding correlation table see SI 11). Overall, participants reported moderate flow state ($M = 5.05$, $SD = 1.09$). Accordingly, in the majority of evening e-diaries, they reported that they had experienced flow at least once (76.6 % of observations). According to the null model, less than 20 % of variability in flow state were due to between-person differences (ICC = 0.18). This dominance of within-subject variability supports our use of ambulatory assessment for measuring changes in flow state (see SI 12 for a depiction of within- and between-subject flow variability over time dependent on condition).

[10] Please note that flow proneness, but not skill-demand-balance were pre-registered as a potential control. When analyzing the data, we realized that we needed to control for this variable since flow depends on presence of a skill-demand-balance (Engeser & Rheinberg, 2008).

[11] We did not include the interaction effects with flow proneness (see Model 4) in this model due to convergence issues.

3.1. Changes in flow state due to intervention type and decision rule

Both the effects of the decision rule and the intervention type interacted significantly with time (Model 2, both $p < .05$) indicating that changes in flow state evolved differently over time depending on conditions. In line with that, including the effect of time and two-way interactions between time and the two predictors of interest (Model 2) significantly improved model fit compared to Model 1 that did not account for these time-related changes ($p < .001$, Table 2). Hence, in the following, we will first report the results of Model 2 in more detail before acknowledging differences in effects when including potential covariates.

For a typical person in the control condition who received prompts every morning, flow state was 5.24 when all other predictors were zero (i.e., at the last observation, for a person with average flow proneness, for an observation with individually average skill-demand-balance). Flow state did not differ significantly between this person and a person from the MC condition ($B_{\text{Type}} = 0.15, p = .357$). However, flow state was significantly lower for a person who received prompts adaptively ($B_{\text{Rule}} = -0.43$, $p = .012$, $d = -0.41$). Also, flow state increased significantly less over time for individuals receiving adaptive prompts (compared to static), $B_{\text{Rule x Time}} = -0.02$, $p < .001$, and significantly more for individuals applying MC (compared to control intervention type), $B_{\text{Type x Time}} = 0.01, p < .050$ (Table 4). Thus, these results confirm our first hypothesis indicating a significant advantage of MC compared to control over time. They do not confirm our second hypothesis that the adaptive compared to the static decision rule significantly increases flow.

3.2. Potential covariates and their effect on flow

While the estimates of Model 2 apply for all observations independent of task type, the estimates of Model 3 apply for observations during work (because task type was coded as 0 indicating working) (see Table 4 for direct comparison between estimates of Models 2 and 3). Whether a person worked or not did not significantly influence flow state ($B_{\text{Task}} = 0.12$, $p = .122$). However, adding the effect of task type to the model (Model 3) significantly improved model fit ($p < .001$, Table 2). This is important because, while the estimates of most effects of interest do not differ in their significance between the results of Models 2 and 3 (Table 4), the two-way interaction effect between time and intervention type is not significant after controlling for the effect of task type. This result indicates that, controlling for the effect of task type, it is not possible to confirm with certainty that MC has a significant advantage over time in comparison to the control.

Since adding flow proneness as a moderator for the effects of decision rule and intervention type on flow change over time (Model 4) or adding a two-way interaction between decision rule and intervention type (Model 5) did not significantly improve model fit ($p = .109$ and $p = .212$, Table 2), we will not discuss the results of Models 4 and 5 further.

Table 2
Model fit information for the linear mixed models predicting state flow.

	df	AIC	BIC	χ^2	$\Delta\chi^2$	dfΔ	p
Null model	3	5416.75	5433.37	−2705.37	–	–	–
Model 1	10	5301.04	5356.47	−2640.52	129.70	7	<0.001
Model 2	16	5285.88	5374.56	−2626.94	27.16	6	<0.001
Model 3	21	5220.02	5336.41	−2589.01	75.86	5	<0.001
Model 4	25	5219.03	5357.58	−2584.51	8.99	4	0.061
Model 5	22	5220.46	5342.39	−2588.23	1.56	1	0.212
Model 6	31	5292.58	5464.39	−2615.29	–	–	–

Note. Chi-square difference tests indicate relative superiority to the next nested model (i.e. Model 1 compared to Null Model, Model 2 compared to Model 1, etc.). Model 5 was compared to Model 3 since it was not nested in Model 4. Model 6 was not compared to the other models with chi-square difference tests since it had a three-level structure instead of two levels. For an overview of models with included random and fixed effects see SI 3.

Table 3
Summarizing visualization of the linear mixed models predicting flow state.

Flow ~	Null Model	Model 1	Model 2	Model 3	Model 4	Model 5
Intervention Type (0 = Control, 1 = MC)		+	+	+	+	+
Decision Rule (0 = Static, 1 = Adaptive)		+	+	+	+	+
Skill-Demand-Balance (Person-mean-centered, Level 1)		+	+	+	+	+
Flow Proneness (Grand-mean-centered, Level 2)		+	+	+	+	+
Time (Observation number, Level 1)			+	+	+	+
Decision Rule x Time (Cross-level interaction effect)			+	+	+	+
Intervention Type x Time (Cross-level interaction effect)			+	+	+	+
Task Type (0 = Working, 1 = Not working)				+	+	+
Flow Proneness x Decision Rule (Level 2 interaction effect)					+	
Flow Proneness x Intervention Type (Level 2 interaction effect)					+	
Flow Proneness x Decision Rule x Time (Cross-level interaction effect)					+	
Flow Proneness x Intervention Type x Time (Cross-level interaction effect)					+	
Decision Rule x Intervention Type (Level 2 interaction effect)						+

Note. Model 6 not depicted due to its 3-Level structure. For model overview including random effects see SI 3.
Null Model = Random-intercept-only Model.
Model 1 = Flow also explained by treatment and major control variables.
Model 2 = Flow also explained by interactions with time.
Model 3 = Flow also explained by task type.
Model 4 = Flow also explained by flow proneness moderation of treatment variables.
Model 5 = Flow also explained by interaction effect of the treatment variables.

One may assume that the significant negative effect of the adaptive decision rule on flow state does not necessarily point to a disadvantage of the adaption. Rather, this finding could indicate that it matters

Table 4
Influence of decision rule and intervention type on flow state over time controlling for skill-demand-balance and flow proneness at baseline.

	Model 2			Model 3		
	Estimate	(*SE*)	95 % CI [LL, UL]	Estimate	(*SE*)	95 % CI [LL, UL]
Intercept	5.24[c]	0.14	4.95, 5.52	5.21[c]	0.14	4.93, 5.49
Rule	−0.43[a]	0.17	−0.77, −0.10	−0.43[a]	0.16	−0.75, −0.10
Type	0.15	0.16	−0.18, 0.48	0.10	0.16	−0.22, 0.42
Time	0.01	0.00	0.00, 0.01	0.01	0.00	0.00, 0.02
Task	–	–	–	0.12	0.08	−0.03, 0.28
Skill-demand-balance	−0.21[c]		−0.29, −0.12	−0.21[c]	0.04	−0.30, −0.13
Flow proneness (baseline)	0.27[c]		0.12, 0.43	0.28[b]	0.08	0.12, 0.43
Rule x Time	−0.02[c]	0.01	−0.03, −0.01	−0.02[c]	0.00	−0.03, −0.01
Type x Time	0.01[a]	0.01	0.00, 0.02	0.01	0.00	0.00, 0.02

Note. Level 1: $n = 1886$ observations; Level 2: $N = 59$ participants. Dichotomic variable for decision rule (0 = static, 1 = adaptive), intervention type (0 = control, 1 = MC), and task (0 = work, 1 = other). Time centered for end of observation period (0 = last observation). Person-mean centered variable for skill-demand-balance. Grand-mean centered variable for flow proneness at baseline. CI = Confidence interval, LL = Lower level, UL = Upper level.
[a] $p < .05$.
[b] $p < .01$.
[c] $p < .001$.

whether participants attended to the prompt for applying the intervention type. To rule out this explanation, we computed an additional exploratory three-level model (Model 6; Level 1: $n = 1886$ observations over day, Level 2: $n = 292$ daily observations, Level 3: $n = 59$ participants). The included predictors were similar to Model 2[12] except for the time variable (number of days instead of observation due to the three-level structure) and an additional predictor indicating whether participants received and then also attended to the prompt in the morning (0 = no,[13] 1 = yes). Since this predictor remained constant over each day, the three-level structure was needed. Results showed that attendance to the prompt did not significantly influence flow state,[14] $B_{\text{Prompt}} = -0.08$, $p = .396$. Most importantly, while controlling for this effect, the adaptive decision rule still significantly negatively influenced flow state compared to the static one ($B_{\text{Rule}} = -0.44$, $p = .008$, $d = -0.41$) (see Table 5 for complete results of Model 6).

3.3. Differences in flow proneness

A one-way ANOVA revealed no significant differences in proneness to experiencing flow at work between the four groups at baseline, $F(3, 55) = 1.19$, $p = .322$, indicating successful randomization of participants to conditions. Since all participants received an intervention, we generally expected increases in flow independent of intervention type and decision rule. In line with that, flow proneness was higher at follow-up compared to baseline over all participants ($M_{\text{Difference}} = 0.27$, $SD_{\text{Difference}} = 0.63$).[15] A one-tailed *t*-test for paired samples (Shapiro-Wilk: $p = .073$) confirmed significantly higher flow proneness at follow-up compared to baseline independent of conditions, $t(57) = 3.31$, $p = .001$.

Table 5
Exploratory results from Model 6 controlling for the effect of prompting.

	Estimate	(*SE*)	95 % CI [LL, UL]
Intercept	5.31[c]	0.16	5.00, 5.62
Rule	−0.44[b]	0.16	−0.76, −0.12
Type	0.12	0.15	−0.19, 0.12
Day	0.06[+]	0.03	−0.01, 0.13
Prompt	−0.08	0.09	−0.27, 0.10
Skill-demand-balance	−0.21[c]	0.04	−0.29, −0.12
Flow proneness (baseline)	0.28[c]	0.08	0.12, 0.44
Rule x Day	−0.15[c]	0.04	−0.23, −0.08
Type x Day	0.08[a]	0.04	0.01, 0.16

Note. Level 1: $n = 1886$ observations over day; Level 2: $n = 292$ daily observations, Level 3: $N = 59$ participants. Dichotomic variable for decision rule (0 = static, 1 = adaptive), intervention type (0 = control, 1 = MC), and prompt (0 = no, 1 = yes). Day centered for end of observation period (0 = last day). Person-mean centered variable for skill-demand-balance. Grand-mean centered variable for flow proneness at baseline. CI = Confidence interval, LL = Lower level, UL = Upper level.
[+] $p < .10$.
[a] $p < .05$.
[b] $p < .01$.
[c] $p < .001$.

3.4. Differences in feedback about intervention type

Descriptive statistics from the feedback questionnaire can be found in SI 6. On average, participants planned to use the intervention type again after the study ($M = 3.19$ on a five-point Likert scale from 0 to 4) with no significant difference due to intervention type ($W = 318$, $p = .085$). However, participants reported significantly less often that they had used the strategy repeatedly per day in the MC compared to the control condition, $\chi^2(1) = 5.28$, $p = .022$. At the end of the study, most participants in the control condition reported that they had fulfilled all their formulated goals, whereas only half of the participants who used MC agreed with that. However, this difference in goal fulfillment was not significant, $\chi^2(1) = 1.96$, $p = .162$.

4. Discussion

In an ambulatory assessment study covering five consecutive workdays, we evaluated the flow-promoting effect of a smartphone-based JITAI that prompts the application of metacognitive strategies in knowledge work. Even though we found that using these strategies generally increased the proneness to experiencing flow independent of the specific type of strategy, our results indicate that in the long-term MC might be more helpful for increasing flow than setting SMART goals. It is important to acknowledge that this long-term benefit of MC was not observable when the influence of current task was considered. In contrast to what we expected, prompting the strategy adaptively, i.e., based on the person's previous flow experiences, was not beneficial for fostering flow state. In the following sections, we will discuss how these

[12] We based this model on Model 2 rather than the better-fitting Model 3 due to problems with model fit (no convergence of the model when task type was included as a predictor).
[13] "No" indicates that participants either did not receive a prompt in the first place (due to the adaptive condition) or they received a prompt but ignored it.
[14] When all other predictors were zero (i.e., last day of observation, average flow proneness, individually average skill-demand-balance, control intervention type).
[15] Although this increase in flow proneness from before to after the intervention indicates the effectiveness of our intervention independent of specific intervention type and decision rule, these changes could also arise because of changes in the understanding of the measure (i.e., for example because participants were more aware of their flow states at the end of the study since they had reported their flow repeatedly over the week). Hence, we do not report the full results on these changes in flow proneness here. The interested reader may find them in SI 5.

results contribute to research and practice and review the limitations of our findings.

4.1. Contributions for research and practice

Our findings contribute to interdisciplinary research on the development of flow interventions for application in everyday life in two major ways. First, we showed for the first time that MC increases flow in knowledge work over the course of five consecutive workdays only. Since applying MC in the morning took only a minute on average and participants reported a high willingness to continue using the strategy after the study, our findings support MC as a user-friendly, digitally applicable, and quickly effective tool that can easily be integrated in everyday life without causing disruptions at work. This flow-promoting effect of MC was emphasized by the finding that it was at least as effective as another goal-setting strategy already found to increase flow (setting SMART goals; Weintraub et al., 2021). While our finding of a significant effect of the intervention type over time indicates that knowledge workers could especially benefit from using MC in the long run, this long-term advantage of MC was not observable when controlling for covariates. Hence, this effect should be interpreted with caution and reevaluated over longer observation periods (see also limitations discussed in section 4.2). Although the difference in goal fulfillment between intervention types was not statistically significant, the direction of the difference indicates that MC might encourage setting preferences in terms of disengagement from goals for which outcomes are at odds with obstacles. Thereby, MC might grant higher autonomy than SMART goal-setting although this does not seem to impact flow state immediately. Possibly, setting SMART goals comes more easily, whereas participants may need a couple of tries to get involved with the more complex procedure of applying MC. Indeed, participants applying MC attended significantly longer to the morning prompt compared to participants setting SMART goals (see SI 7 for additional analysis). Importantly, while participants used MC significantly less often per day compared to SMART goal-setting, flow state increased at least as much over time in the MC compared to the control condition. Hence, our results indicate that even though it takes longer to follow the MC sequence, this strategy may need to be applied less often to be at least as effective as setting SMART goals (Weintraub et al., 2021). This is especially promising when aiming for applying the intervention in everyday knowledge work because multiple interruptions over the day may not be necessary.

As a second major contribution and in contrast to what we expected, our findings show that providing the intervention independent of the state of the user was more helpful for promoting flow than use of a JITAI. This discrepancy may be attributed to the fact that participants in the static condition received significantly more prompts than those in the adaptive condition, due to the experimental manipulation. Consequently, they were exposed to the strategy with greater frequency and may have derived greater benefit from its flow-promoting effect. This positive effect of the static compared to the adaptive prompt seems to contradict the assumption that static interventions cause intervention fatigue, thereby decreasing interventional effectiveness (Heckman et al., 2015; Nahum-Shani et al., 2018). However, the process of habit formation may offer insight into why this effect did not appear in our study. Research agrees that consistent repetition of a behavior in stable contexts serves as the basis for habit formation (Carden & Wood, 2018; Lally & Gardner, 2013). In our study, the static condition provided such a stable context in that participants expected to receive a prompt every morning. By contrast, in the adaptive condition, they were not aware on which days they would receive a prompt. Hence, by providing regular reminders, the static intervention might have facilitated repetition, in our case application of the metacognitive strategy, which in turn increased flow. Indeed, Stawarz et al. (2015) found that use of reminders in smartphone-based applications facilitates repetition of wanted behaviors. Importantly, in our study, the advantage of prompting strategy use every morning (instead of adapted to the user) was independent of whether participants attended to the prompt. Hence, we assume that the expectancy to receive a regular prompt was decisive for strategy repetition that then increased flow.[16] Importantly, research indicates that habits do not necessarily form due to repetition alone. They only evolve when behavior becomes automatic (Carden & Wood, 2018; Lally & Gardner, 2013). In line with that, the increased repetition of behaviors due to the smartphone-based reminders in the study by Stawarz et al. (2015) was not associated with increases in automaticity. Instead, researchers cautioned against the potency of regular reminders to cause dependencies, in that users might then solely engage in the behavior when reminded (Renfree et al., 2016; Stawarz et al., 2015). This ultimately increases the likelihood to disengage from app usage, then also undermining the targeted habits (Renfree et al., 2016). In the next section, we will elaborate why the duration of our study does not allow to assess whether the potential increases in repetition due to the regular reminders in the static intervention also bore this risk and impeded long-term strategy use.

4.2. Limitations and future research

We only assessed changes in flow state over the course of five days. Hence, even though in our study, the static intervention increased flow state compared to the JITAI and became more effective over time, this linear effect is only based on the data from the observation period. Since our results indicate that the main effects of the intervention type and the decision rule change over time, this time period might have been too short to allow final conclusions. For example, even though the effect might reverse in the long term due to increases in intervention fatigue, our study period does not allow to assess these potential shifts. Thus, future research should investigate the long-term differences in promoting flow between a JITAI and a static intervention. Concurrently, an evaluation of an extended observation period would allow the estimation of the discrepancies between the two intervention types over time with greater precision. This is particular crucial given the lack of confirmation of a long-term advantage of MC in comparison to setting SMART goals when controlling for covariates. On the same note, we cannot assess whether the static intervention increases repetition of strategy at first but causes participants to neglect the application in the long-term. Based on earlier research indicating that strengthening interconnection between wanted behaviors and contextual cues increases habit formation compared to reminders alone (Stawarz et al., 2015; Wicaksono et al., 2019), we suggest future research to examine whether letting participants choose a contextual cue for applying the mental strategy (e.g. applying the strategy every time when starting the computer) increases strategy application, thereby enhancing the effect on flow.

The negative effect of the JITAI compared to the static intervention could also imply that our choice of the tailoring variable was not ideal. This variable required participants to provide a retrospective estimation of their daily flow. This may be particularly problematic in the case of affective experiences such as flow, given that these experiences are differently remembered than momentarily lived (Robinson & Clore, 2002). Although the correlation between the repeated flow reports throughout the day and the evening report yielded a similar estimation of daily flow by the two measures, it is not possible to discount the potential influence of recall bias on the tailoring variable. Importantly,

[16] One potential reason for this finding would be differences between conditions regarding the time spent with responding to the morning prompt (i.e., the time from opening to closing the query). However, the length of attendance to the prompt did not differ significantly depending on decision rule (see SI 7 for complete results of this exploratory analysis) indicating that participants did not attend to the prompt more shortly in the adaptive compared to the static condition.

another important limitation arose when participants did not answer the tailoring variable because we then lacked information for whether to present the prompt. Since we decided to provide the prompt in this case, this could have confounded the effectiveness of the adaptive mechanism. However, when excluding these observations from the dataset, the directions of effects did not change (SI 8). Nevertheless, future research could use more objective measures for the tailoring variable so that it does not depend on user compliance. For example, earlier research suggests that heart rate variability may inform about flow likeliness by indicating if a person is relaxed or stressed (e.g. Rissler et al., 2018; Tozman et al., 2015). Since novel technologies allow measurement of such physiological data in real-time using non-obtrusive devices such as smartwatches (Alugubelli et al., 2022; Dobbs et al., 2019), this approach would be easily integrable in everyday work.

Apart from these limitations regarding the adaptive mechanism, the just-in-time provision of support is a major determinant of the effectiveness of JITAIs (Nahum-Shani et al., 2018). In our study, we provided the strategy prompt in the morning assuming that this would be before participants started to work, thereby not intervening with their current flow. However, at the end of the study, some participants gave feedback that they worked different hours. Then, the morning prompt would either interrupt them or cause them to apply the strategy hours before they started working. Hence, we recommend incorporating individual working hours in the scheduling of the prompts or tracking working activities through objective indicators such as log data, thereby improving the adaptivity as well as the just-in-time provision of support.

While we concentrated on the direct effect of the JITAI on flow state, research has repeatedly demonstrated that flow is associated with a number of other work-related factors (Peifer & Wolters, 2021), including enhanced performance, elevated energy levels, and increased creativity (Demerouti et al., 2012; Engeser & Rheinberg, 2008; Zubair & Kamal, 2015). Thus, these factors may serve as distal indicators of the JITAI's effectiveness. In fact, we initially measured self-reported work performance and stress at the end of each workday. However, we were unable to conduct mediation analyses for the effect of the JITAI on these outcomes via flow state due to limited statistical power. This was because these variables were assessed on a daily basis, rather than repeatedly each day, as was the case for flow state. This significantly limited the sample size at Level 1. We encourage future research to proceed with these mediation analyses by increasing the number of measurements for the distal outcome variables. To minimize participants' burden, we recommend that the focus be narrowed to a single potential work-related outcome.

4.3. Conclusions

Despite these limitations, our findings from an ambulatory assessment study show that smartphone-based assistance can support flow in knowledge work by encouraging the use of metacognitive strategies. While the use of these strategies tends to enhance the likelihood of experiencing flow over the course of five workdays regardless of the specific type of strategy employed, our findings suggest that MC may be especially effective in fostering flow over the long term. In addition, our study highlights that adaptive support does not necessarily excel support independent of the user when aiming for promoting flow in knowledge work. Due to the exploratory nature of our intervention design, we argue though that this finding should not be interpreted as general advice against using adaptive interventions for promoting flow. Rather, we recommend evaluating longer periods of intervention application to examine differences between adaptive and static support regarding habit formation and intervention fatigue.

Statements and declarations

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CRediT authorship contribution statement

Karen Bartholomeyczik: Writing – original draft, Visualization, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Michael T. Knierim:** Writing – review & editing, Investigation, Conceptualization. **Christof Weinhardt:** Writing – review & editing, Supervision, Resources, Funding acquisition. **Gabriele Oettingen:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2024.100488.

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