Improving Work-Nonwork Balance with Data-Driven Implementation Intention and Mental Contrasting

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Work-nonwork balance is an important aspect of workplace well-being with associations to improved physical and mental health, job performance, and quality of life. However, realizing work-nonwork balance goals is challenging due to competing demands and limited resources within organizational and interpersonal contexts. These challenges are compounded by technologies that blur the boundaries of work and nonwork in the *always-on* work cultures. At an individual level, such challenges can be subsided through the effective application of self-regulation techniques, such as *implementation intentions and mental contrasting* (IIMC). Further supporting these techniques through reflection on personal data, we implement the idea of *data-driven IIMC* into a self-tracking and behavior planning system and evaluate it in a three-week between-participant study with 43 information workers who used our system for improving work-nonwork balance. We find evidence that reflection on personal data improves awareness of behavior plan compliance and rescheduling, which are important in realizing work-nonwork balance goals. We also observe the value of *micro-reflection*, reflection on limited data of the very recent past, for IIMC. Our findings highlight opportunities for automation in data collection and sense-making and for further exploring the role of data-driven IIMC as boundary negotiating artifacts in support of work-nonwork balance goals.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; *Interactive systems and tools.*

Additional Key Words and Phrases: Implementation Intention, Mental Contrasting, Goal-Setting, Goal Realization, Behavior Change, Work-Nonwork Balance, Reflection, Personal Data, Workplace Well-being

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1 INTRODUCTION

Workplace well-being is an important public health priority that has a cascading impact on individuals, families, businesses, and the economy [97]. Work-nonwork balance plays a critical role in achieving workplace well-being [15, 33, 94, 102], and positive work-nonwork balance is associated with greater physical and mental health [68, 104, 106], higher job performance [59], quality of life [48], and job satisfaction [50]. However, over 10% of employees globally work 50 hours or more in paid work per week [81], most American employees report experiencing early signs of burnout [70], and multiple surveys across sectors report that over half of Americans experience poor work-nonwork balance [45, 98].

Work-nonwork balance issues have become more prevalent, consequential, and pressing due to new information and communication technologies (ICTs) and the associated *always-on* work cultures that have enabled blurring of boundaries [29, 69]. Studying the role of technology in supporting or harming workplace well-being has been the topic of research in human-computer interaction (HCI) and computer-supported collaborative work (CSCW) [1, 14, 25, 27, 36, 93]. Although realizing well-being goals is generally challenging [44], competing demands due to constrained resources, limited control, organizational policies, and culture exacerbate the difficulties in realizing work-nonwork balance goals [17, 30, 39, 40, 47] and in formulating effective plans for bettering work-nonwork balance [78]. While many challenges to work-nonwork balance are beyond individuals' control, empowering them to make the most of existing situations can mitigate some of their burdens. Therefore, further research is necessary to explore how technology can support people in responding to challenges encountered while improving their work-nonwork balance goals.

Self-regulation techniques such as implementation intention (II) and mental contrasting (MC) are particularly applicable in this context [78]. IIs are 'if-then' plans that connect a critical situation to goal-directed actions; actions that help one achieve the desired goal (e.g., "if I crave sugary snacks, then I will eat a healthy fruit instead" for the goal of "healthy eating"). MC asks people to elaborate on their desired state and identify the obstacles standing in the way of realizing that state (e.g., "disorganized notes" is an obstacle to the desired future of "excelling in exam"). II and MC have been successfully used for behavior change in a variety of settings and are especially powerful when used in combination [75], where if-then plans are formed around obstacles (if-part) and actions to prevent or overcome them (then-part).

Relevant prior HCI research has considered supporting II by enhancing the execution of II plans via reminders [8, 85] or recommending automatically generated II plans based on personal data [31]. However, a key challenge in the effective application of II or IIMC is *forming* quality behavior plans [87, 100]. With respect to IIMC in particular, people have to identify *their own* obstacles and decide on actions doable *for them*, both of which are non-trivial tasks. There is existing evidence that people need support to recall specifics of deviations in expected behaviors [19] as well as failures in following planned behaviors [105]. Decision-making around suitable actions is similarly challenging [38]. These challenges are intensified in the context of work-nonwork balance given the complexity of demands and the steps for responding to them [78].

Towards addressing this gap, we explore reflection on personal data as a way of scaffolding IIMC plan creation for achieving work-nonwork balance goals. We hypothesize that this approach can improve the identification of personally relevant obstacles and doable actions, given its promise in increasing awareness of one's behaviors and context [22, 105]. This paper reports our study testing this hypothesis. Specifically, we address the following research questions:

RQ1 Does data-driven self-regulation via IIMC lead to a better understanding of obstacles in the way of work-nonwork balance and the opportunities to respond to these obstacles?

RQ2 Does data-driven self-regulation via IIMC improve perceived work-nonwork balance during the study? If so, does the improvement surpass that of alternatives?

To address these research questions, we designed a system that allowed people to collect personal data and reflect on it as they created behavior plans based on IIMC instructions. We then evaluated this system in a three-week between-participant study with 43 participants in four groups: the group who used data-driven IIMC planning (DDIIMC) compared to groups who used only data (DD), only IIMC instructions (IIMC), or neither (basic control). We find that DDIIMC group significantly outperforms others in several tasks pertaining to the pursuit of work-nonwork balance: they are more aware of their plan compliance and more capable of rescheduling their plans as personal or socially-imposed changes arise. We also find the importance of reflection on the recent past (micro-reflection) in improving these tasks as well as measures of work-nonwork balance and time-management. We discuss the implications of our findings in terms of future design opportunities to support data-driven IIMC at work along with considerations for the collaborative and multi-stakeholder nature of this context. In summary, our contributions are:

- We propose *data-driven IIMC* to support decision-making in planning for goal realization. We then design a tool for drawing insights from personal data to guide users in deciding what actions to take as well as when and where to take them (Section 3).
- We evaluate data-driven IIMC through a three-week between-participant experimental study with 43 participants (Section 4).
- We confirm that reflection on data improves performance on tasks that underlie IIMC application, such as plan compliance awareness and rescheduling (Section 5).
- We present design implications and considerations for incorporating data in decision-making for IIMC (Section 6).

2 BACKGROUND

Our work is informed by prior research in management sciences, organizational psychology, CSCW, and HCI to understand the role of technology-supported self-regulation techniques towards achieving work-nonwork balance goals. We highlight the importance of supporting work-nonwork balance and workplace well-being where tensions across roles, demands, and organizational culture may introduce obstacles in achieving the desired work-nonwork balance goals, despite recent technology research and innovations to address workplace well-being. We then introduce implementation intention and mental contrasting (IIMC) as a technique to overcome some of the challenges in goal realization, with a gap in prior research for technology enhancements to support IIMC formation. Finally, we build on prior work on technology-facilitated reflection on personal data as a promising approach to complement IIMC.

2.1 Work-Nonwork Balance and Well-being at Work

Well-being in the workplace is important for work engagement, productivity, and job satisfaction [91, 96]. A positive organizational culture that promotes employee well-being is associated with positive interpersonal relationships [3, 32], reduced absenteeism, and reductions in related costs [24, 67]. One of the key facets of well-being in the workplace is work-nonwork balance [33, 94, 102]. Delecta defines work-nonwork balance as an individual's ability to meet their work and personal commitments, as well as other non-work responsibilities and activities [28]. The inability to strike the right balance between work and nonwork roles or demands can lead to over-commitment to fulfill the responsibilities of both [30], with detrimental effects on the overall well-being of workers [68, 104] due to the spillover of stress between work and life outside of work [49].

Work-nonwork balance sits along a continuum between integration (i.e., blurred boundaries) and segmentation (i.e., strong boundaries), based on the degree that work is kept separate from nonwork [2, 4, 13]. Although work-nonwork balance has been conceptualized as an individual preference, scholars argue that work-nonwork balance should not be portrayed as only a matter of individual choice. It is a socio-cultural phenomena that should rather be jointly considered with organizational policies, norms, and expectations [10, 39, 79]. For example, organizational policies such as flexible work arrangements have been shown to be effective in improving work-nonwork balance [9] and organizational culture has been shown to influence the utilization of work-nonwork balance programs [12]. Therefore, work-nonwork balance goals, while personal and idiosyncratic in nature, are affected by the surrounding work environments, such as work demands, culture, social dynamics, or flexibility.

In recent decades, the proliferation of information and communication technologies (ICTs) that enable virtual work, the use of personal technologies at work and vice-a-versa, and the always-on work culture have all contributed to an increased blurring of work-nonwork boundaries [29, 69]. Such blurring of boundaries has been further exacerbated by the mass transition to remote work during the pandemic [18, 86]. Unfortunately, the flexibility that is afforded by ICTs has also made it more difficult to achieve work-nonwork balance [23, 90, 93]. Multiple surveys across sectors report that over half of Americans experience poor work-nonwork balance [45, 98]. Therefore, supporting work-nonwork balance in the digitized world has become a pressing need. It requires work on multiple fronts, from empowering individuals to take actions that better their work-nonwork balance, to getting at the social and cultural factors that lead to worsening work-nonwork balance. In this work, our focus is on enabling individuals' actions to improve their work-nonwork balance within the bounds of external factors.

Workers are genuinely interested in improving their work-nonwork balance, but struggle to do so [46]. Realizing well-being goals is generally challenging [44], and is even more so in the context of work-nonwork balance because high demands and external pressure lead to competing goals and because people are particularly vulnerable to giving in to more pressing needs [78].

Literature in HCI, CSCW, and ubiquitous computing has shown extensive interest in understanding and supporting worker well-being [1, 25, 56, 58, 92]. For example, Das Swain et al. studied how the routine-fit of employees with their workplace associated with employee functioning and well-being [27]. Rudnicka et al. proposed a tool for promoting flexible social norms of break-taking at work for remote workers [93]. Cambo et al. [14] developed a mobile application, BreakSense, to promote mobility during work breaks, and examined how that impacted people's sense of completion and readiness to work [14]. Epstein et al. studied the relationship between work breaks and productivity through a self-reflection tool of summarizing breaks [36].

Our work builds on the above body of research to design and evaluate a tool to support work-nonwork balance, and situates itself in HCI and CSCW's long-term interest in the socio-organizational nature of worker well-being technologies. In particular, we implement a specific form of self-regulation technique (implementation intention and mental contrasting) into a self-tracking and behavior planning system and conduct a longitudinal evaluation of its effectiveness in improving work-nonwork balance.

2.2 Implementation Intention and Mental Contrasting

Goal setting and realization are the primary predictors of health behavior change with the latter explaining much of the variations in goal achievement [44]. However, goal realization poses challenges for many people; about half the people with intentions to engage in health behavior fail to do so as they cannot successfully translate their intentions to actions [80, 95]. There are three processes underlying this intention-action gap: viability, activation, and elaboration of intentions.

Intention viability describes how abilities, resources, and opportunities available to a person influence whether they have control over certain behaviors. Intention activation is the process by which situational demands impact cognitive and motivational resources and thereby the salience and intensity of intentions. There are often conflicting goals and people are particularly inclined toward more enjoyable or pressing alternatives. They either deprioritize the goals they initially set in favor of those alternatives or forget about the initial goals altogether. Intention elaboration refers to the role that the clarity around actions and contextual factors plays in making goals feasible. Behavior change for health and well-being is often a complex sequence of actions. Failure in identifying these actions and the means to perform them undermines goal attainment [87].

Implementation intention (II) and mental contrasting (MC) are self-regulation techniques that support goal realization by mitigating the processes that underlie the intention-action gap [75]. While goals are specifications of a *want* ("I want to do/achieve X"), IIs are if-then statements that specify the *when*, *where*, and *how* of achieving a goal. They take the form "if situation Y happens, I will do [goal-directed] action Z" and connect situational cues to specific actions. For example, "If it is break time, I'll walk down to lobby" for the goal of "being physically active". The act of creating IIs mitigates the elaboration challenge as the deliberation on the relevant actions and their means is a part of the II plan creation process. By connecting specific situations to actions, the planning process becomes more focused on available resources, which helps mitigate viability challenges to the extent possible, e.g., by taking into account the constraints imposed by social and cultural factors. Forming this connection additionally supports maintaining goal activation levels as control of the response is delegated to the presence of the situation [87].

MC involves thinking about a desired future (e.g., "excelling in an exam") and juxtaposing it with the current reality that impedes achieving that future (e.g., "disorganized notes") [75]. Doing so increases motivation for action if there is a high expectation of achieving the desired future [75]. Heightened motivation subsequently supports goal pursuit [66]. The association between future and reality additionally focuses attention on dealing with reality and the instrumental means for it [76], which are important for addressing viability and elaboration challenges in goal attainment.

II and MC have successfully supported goal realization in a variety of domains such as health [26, 87], education [5, 42], or interpersonal problems [43, 77]. They provide greater benefits when combined [75]. MC complements II by providing a concrete process for forming if-then plans, where obstacles form the if-part and overcoming them forms the then-part. It thus mitigates the challenge of plan formation in applying II [87]. II, on the other hand, complements MC by facilitating the process of overcoming difficult obstacles through explicit planning [75]. The combination of II and MC (IIMC) is particularly well-suited for realizing work-nonwork balance goals given they can address challenges in viability (e.g., constraints in time, energy, or other resources available to the individual), activation (i.e., competing goals), and elaboration (e.g., changing situations) that arise in this context. In fact, IIMC has successfully supported the pursuit of the related goal of time-management [76].

However, it is challenging for people to use IIMC technique without additional support in forming IIMC-based behavior plans [100]. It is non-trivial to effectively identify relevant obstacles along with the actions that can overcome or prevent the obstacles. Without additional support, people have to rely on memory to achieve these tasks.

Meanwhile, much of the past related work in HCI is concerned with supporting the execution of II plans. For example, Pinder et al. [85] explore how a context-aware smartphone app can support people by automatically detecting critical situations and reminding the user of the actions to take. Similarly, Bharmal et al. [8] explore the use of peripheral reminders to enhance the activation of goal-directed actions to increase physical activity. Both of these pieces of work [8, 85] focus on enhancing the link between situations and actions in II plans rather than supporting the plan creation itself. Dogangün et al. [31] model daily routines to automatically identify and recommend timeslots or situations that can be used as critical conditions in IIs for physical activity; while this design addresses plan creation, it neither supports users in taking control of their time nor help identify obstacles – a critical activity in interpersonal contexts such as the workplace. Addressing these gaps in technology support for IIMC, the focus of our work is on empowering workers to identify relevant obstacles and actions within their individual and organizational contexts with full agency. We draw upon affordances of reflection on personal data toward this objective.

2.3 Reflection on Personal Data

Reflection on personal data has long been considered a practice to support goal achievement [37, 62]. Reviewing and interacting with data allows people to go through stages of reflection from revisiting their behavior patterns to explaining them to exploring various relationships [19]. This process increases people's awareness of their behavior and leads to insights [19] that are instrumental in making decisions on the actions to take [62] and in coming up with personalized plans [60].

Increasing awareness is particularly important because people are prone to underestimating their deviations from planned behavior [105] or fail to recall specifics of these deviations [19]. Awareness of problematic behaviors, including failures in following behavior plans, is an appealing affordance for IIMC technique, where the focus is on identifying deviations from a desired state.

Insight-driven planning is another appealing affordance of reflection for IIMC in the highly dynamic context of work-nonwork balance. As Niess and Woźniak [74] demonstrate, reflection on personal data empowers individuals to adjust to the changes they experience in daily life. More broadly, reflection on past experience enhances understanding of the circumstances and the relevant resources and behaviors for addressing them [34, 52].

In summary, the challenges of pursuing work-nonwork balance goals call for enhanced self-regulation support. Combining reflection on personal data with IIMC is potentially a promising self-regulation strategy in this context.

3 SYSTEM FOR DATA-DRIVEN IIMC

Our objective is to support decision-making in realizing work-nonwork balance goals through a reflective process, whereby users draw insights from their personal data to decide *what* actions to take as well as *when* and *where* to take them within a combined framework of implementation intention and mental contrasting (IIMC). We do this by developing a system that allows users to review their personal data to examine their work-nonwork balance state, identify obstacles that hinder their desired state, and discover opportunities to prevent and overcome obstacles. Our system consists of (1) an active reporting tool (Section 3.1) to collect data on activities, whereabouts, and progress toward work-nonwork balance plans and (2) a behavior planning tool (Section 3.2) that facilitates reflecting on data within IIMC framework.

3.1 Active Reporting of Activities, Locations, and Progress

We designed a mobile-friendly web interface for active reporting of daily activities and whereabouts as well as progress toward plans for improving work-nonwork balance (Figure 1). Participants customized the interface with the common activities and locations that were applicable to them on a day-to-day basis. They could also update these settings whenever a new activity or location became relevant. A Microsoft Teams chatbot reminded participants five times a day during waking hours to log information over 30-minute intervals for the past 3-4 hours. We allowed back-filling of information for up to a day in the past if participants missed the chance to react to the reminders. Past work on experience sampling informed our choice for the frequency of reminders and the window of logging. Specifically, five daily experience sampling reminders enable high recall and

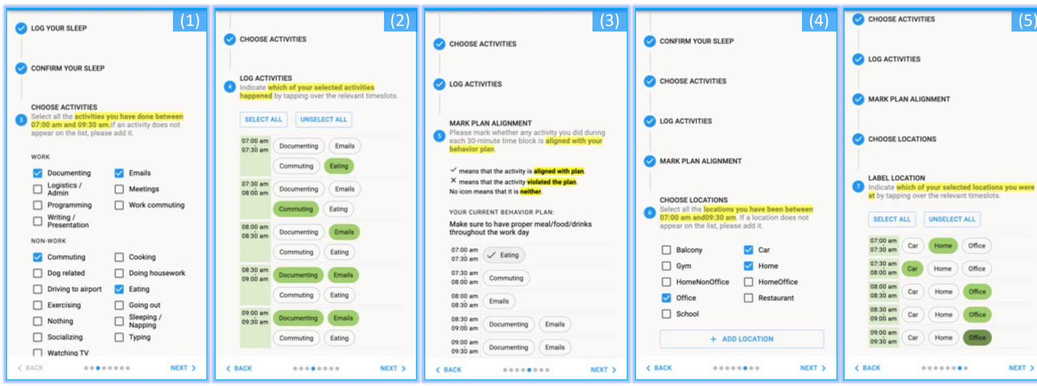

Fig. 1. Interface for Active Reporting of Activities, Locations, and Whereabouts. From left to right: (1) participants selected the activities they engaged in within the specific time window (7:00am to 9:30am in the example) from a customized list of activities. (2) They then marked the activities that happened during each 30-minute time slot (second to left) and (3) decided if their activities were aligned with their behavior plan ('Make sure to have proper meals/food/drink throughout the work day' in the example; middle image). (4) Next, they selected relevant locations to (5) mark per 30-minute timeslots (last two images).

are not too frequent to be disruptive over extended periods (three weeks and above) [20]. Moreover, recalled activities within a day are a reliable representation of time use as noted by Kahneman et al. [54]. The choice of 30-minute granularity kept reporting burden less than 2 minutes per 3-4 hours of reporting, the typical interval between consecutive reminders.

We collected activity, location, and progress data to support IIMC-related activities where users need to understand their actions and the context for those actions. We chose active reporting over passive sensing of data (e.g., through automatic activity or location detection) as active data better support us in establishing whether or not reflection on personal data can help with the more successful application of IIMC. Active reporting minimizes the risk of inaccuracies in passive sensing or data errors, which compromise our ability to conclude if reflection on historical data is beneficial for IIMC. Active reporting is a time-intensive activity that is tenable only for short periods of time, usually in experimental settings [99]. However, given the exploratory stage of our research, we aimed to investigate the feasibility of our approach under ideal circumstances and collect insights on requirements to strive for under more realistic situations (e.g., data granularity, or necessary data sources). In Section 6.3, we discuss the potential for our approach to be augmented with passive sensing.

3.2 Behavior Planning through Reflection on Historical Personal Data

We designed our desktop-friendly planning tool to help users understand their work-nonwork balance state and identify opportunities and actions to improve it. It comprises four key elements: instructions, filters, calendar, and summary (Figure 2):

Instructions. We provide scaffolding for reflective thinking as a series of instructions that appear on the left side of the interface (Figure 2a). We first invite users to think about their desired work-nonwork balance state. We next ask them to use their data to consider their current work-nonwork balance state against the desired, identify obstacles in the way of achieving their desired state, and explore opportunities for addressing these obstacles. We then guide users to use these insights for

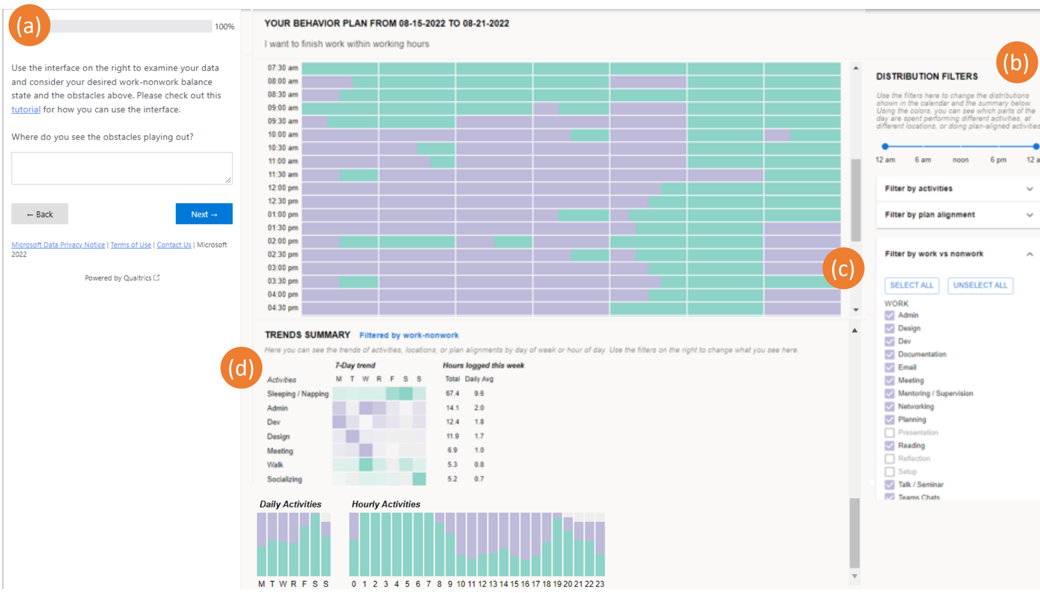

Fig. 2. Data-Driven Behavior Planning Tool Interface. (a) IIMC instructions were given on the left. (b) Participants could choose one of work vs. nonwork, activity, location, or plan alignment filters to get different views of their data. (c) The calendar in the middle displayed data of interest across days of the week and times of the day. In work vs. nonwork view, purple slots represent work while green slots represent nonwork. Slots are split into purple and green halves if activities of both types were reported in them. (d) The tool displays different summary information below the calendar. These include total and average reported hours, distribution of time spent on activities each day (the longer the time, the darker the day under '7-Day trend'), across the week (the 'Daily Activities'), and across the day (the 'Hourly Activities'). Observe that both calendar and Hourly activities show work hours typically start between 8-9 am on workdays.

creating if-then statements that describe behaviors for preventing or overcoming obstacles. This process is detailed in Figure 3.

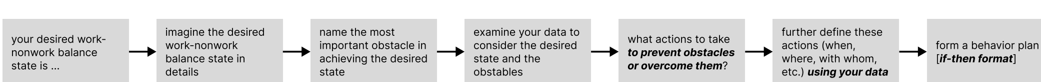

Fig. 3. Instructions for Data-Driven Implementation Intention with Mental Contrasting.

Filters. We enable participants to select and view their data based on aspects such as times of day, specific activities, work vs. nonwork, locations, and progress along their plans through various filters on the right side of the interface (Figure 2b). Calendar and summary information is updated per the choice of filters (see Figure 6 and Figure 7).

Calendar. The interface displays the distribution of the filtered data across days of the week and times of the day (Figure 2c). Slots are color-coded based on the content being viewed. For example, work slots appear in purple while nonwork slots appear in green under work vs. nonwork filter.

Summary. Aggregate information over the week (total and average time), across days of week (7-day trend and daily graph), and hours of day (hourly graph) appear below the calendar (Figure 2d).

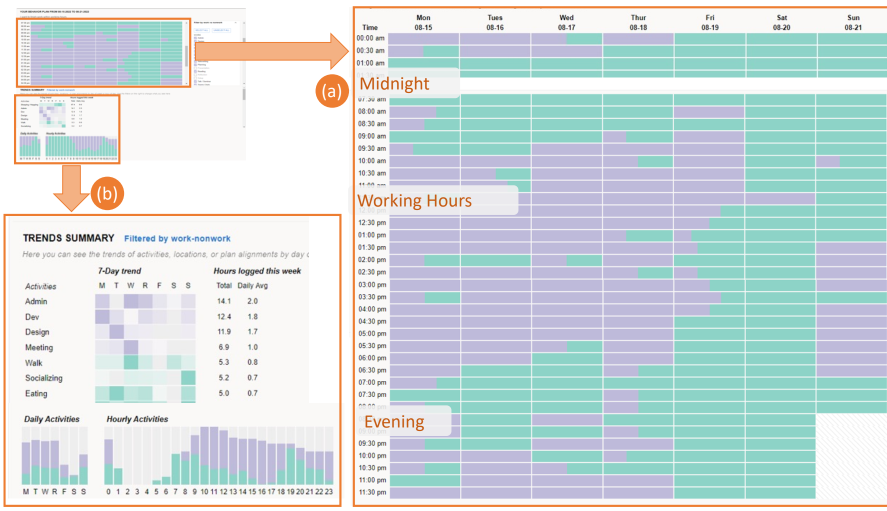

Fig. 4. Work-Nonwork Balance View of How Time is Spent. (a) Work (purple slots) appear after midnight, during working hours, and into the evening. (b) Admin then Dev are the top activities in total hours logged (14.1 and 12.4 respectively).

3.2.1 Design Rationale. We incorporated the above elements following different design patterns that previous work had identified as beneficial for reflection [7]. These include visualizations (calendar and summary), statistics (summary), textual prompts and questions (instructions), and refining and revising different aspects of data (filters). Our design assumes the availability of personal data about user activities, whereabouts, and progress, operationalized as alignment with and violations of existing plans for achieving goals (see Section 3.1 for details on the interface we used to get this information for the purposes of our study).

3.2.2 Walkthrough. Below, we demonstrate the use of different elements of the planning tool with a walk-through. For example, let us follow a software developer whose goal for improving work-nonwork balance is to ensure they finish work within working hours and spend more time on non-work activities, such as listening to the audiobook of a fantasy novel. The instructions on the left (Figure 2) ask the user to draw from their data to (1) consider their desired work-nonwork balance state as well as their current behaviors, (2) identify obstacles to finishing work in time and carrying out nonwork activities of interest, then (3) come up with a behavior plan to prevent or overcome those obstacles, i.e., to decide *what* actions to take as well as *when*, *where*, and *how* to take them. The user is specifically instructed to examine how and where they spend time and how well their behaviors align with their plans.

How Is Time Spent? There are multiple ways available to the user to examine how time is spent. Filtering data by work vs. nonwork, we can see work is happening after midnight, during work hours, and into the evenings in our example (Figure 4a). 7-Day trends offer a ranked summary of time on various activities. Administrative, then development work takes most of the time for the hypothetical software developer (Figure 4b). Filtering by these two activities, one can see administrative work slots clustering earlier in the workdays and development work slots usually starting later in the afternoon (Figure 5a). The hourly activities chart corroborates this observation, where larger segments for administrative work appear during early work hours, whereas larger segments of development work appear during late evening hours (Figure 5b). These observations

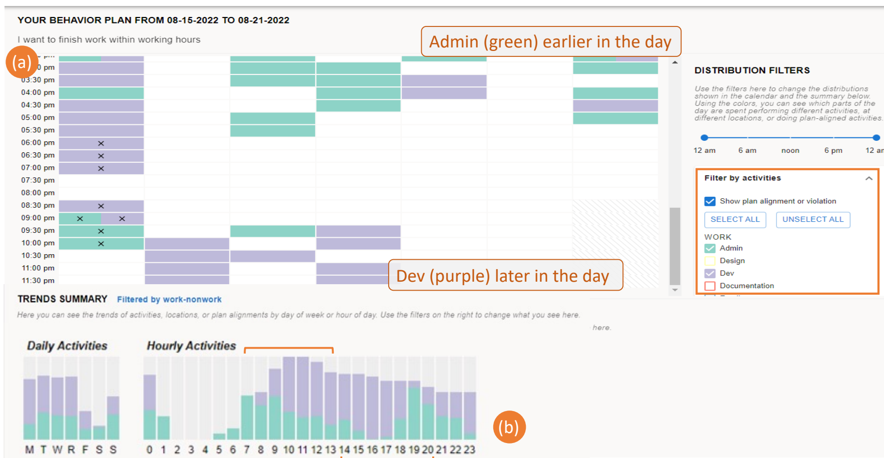

Fig. 5. Activity View of How Time is Spent. Only Admin and Dev are selected of all activities in the activity view filter. (a) Admin (green slots) clusters earlier in the day, while Dev (purple slots) appears later in the day. (b) Larger green segments before 10am indicate more time is spent on on Admin than Dev early in the day. Dev work is most prominent in later hours of the afternoon (6-8pm).

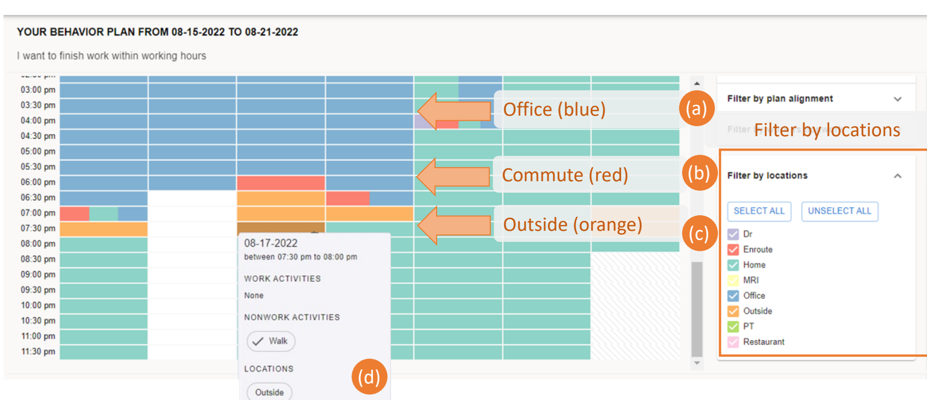

Fig. 6. Location View of Where Time is Spent. (a) Blue slots show time spent at office during working hours. (b) Red slots indicate up to 30 minutes of commute 6-7pm. (c) Orange slots suggest time is spent outside after the commute. (d) Walking is the reported activity for time spent outside when hovering over the orange slots.

highlight an important obstacle to finishing work on time: spending too much time too early on less important work leads to working in the evenings or even after midnight.

Where Is Time Spent? Filtering data by location, we can see typical places one spends time at different hours (e.g., being at the office during work hours on workdays; Figure 6a), timing and duration of commutes (Figure 6b), and patterns of transitions from one place to another (e.g., spending time outside after office Figure 6c). Hovering over the time slots to examine the activities we can additionally see common activities at a location (Figure 6d). In our example, walking is the most common activity when spending time outdoors. Knowledge of whereabouts and common activities can help carve out time for activities that are not currently happening. The software developer in our example might decide to listen to audiobooks while walking.

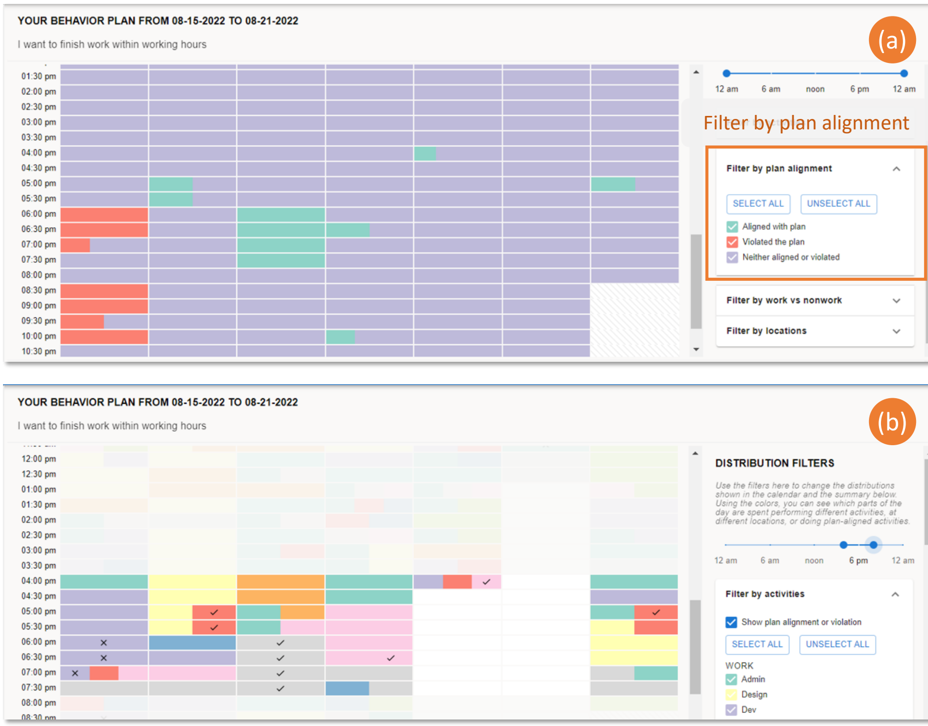

Fig. 7. View of Alignments and Violations of Planned Behaviors. (a) Alignment is reported for several days after 5pm under plan alignment view. (b) Examining the window of time where alignments are reported under activity view, shows a recurring pattern of gray slots (documentation).

Do the Existing Behaviors Match the Desired Behaviors? Filtering data by plan alignment, we can examine the timing and distribution (Figure 7a) of both alignments and violations of the existing plans for achieving work-nonwork goals. We can further examine aligning/violating activities by overlaying this information within filter by activities (Figure 7b). In the example, there are no violating behaviors when the end of the work day is spent on documenting work as a way of re-evaluating progress and re-prioritizing the remaining tasks. This insight highlights the opportunity for supporting the desired behavior by reinforcing the helpful behaviors (i.e., documentation).

4 EVALUATION STUDY

The primary objective of our research was to examine if we can help individuals improve their work-nonwork balance through data-driven self-regulation based in implementation intention and mental contrasting (IIMC). We thus conducted a three-week between-participant study to address the following research questions:

- **RQ1** Does data-driven self-regulation via IIMC lead to a better understanding of obstacles in the way of work-nonwork balance and the opportunities to respond to these obstacles?
- **RQ2** Does data-driven self-regulation via IIMC improve perceived work-nonwork balance during the study? If so, does the improvement surpass that of alternatives?

We asked study participants to create behavior plans to improve their work-nonwork balance and compared outcomes (Section 4.2) among four groups: (1) Data-driven IIMC (DDIIMC) group who used the data-driven planning tool (Section 3.2) to draw insights from their data and create behavior plans within the IIMC framework, (2) IIMC group who were given standard IIMC instructions but did not reflect on their data to create their behavior plans, (3) Data-driven reflection (DD) group who used the visual elements of the interface but were not given IIMC instructions in plan creation, (4) Basic control group who neither reflected on their data nor received IIMC instructions. Basic control and DD groups were given instructions in positive thinking for creating their plans, which allowed us to control for the IIMC effect (i.e., we ensured the plans in these conditions are not based in IIMC, e.g., because of prior training). Moreover, positive thinking instructions are typically used in empirical studies of IIMC in comparison groups (e.g., [76]). Figure 8 illustrates the particulars and differences in the four conditions. Having these conditions should allow us to separately examine the contribution of personal data and IIMC instructions to the observed differences in outcomes.

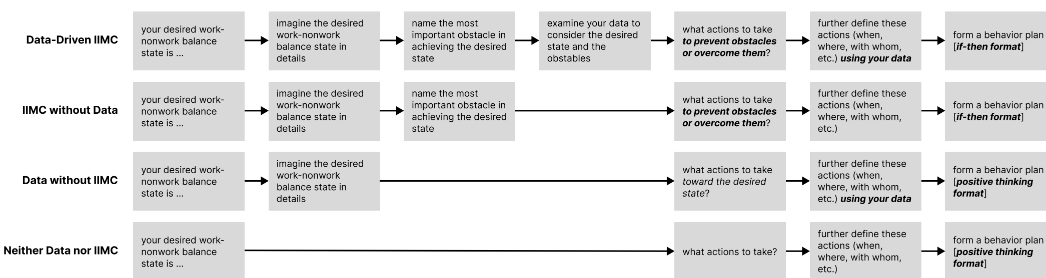

Fig. 8. Intervention Instructions Given under Different Study Conditions. The top row illustrates the full data-driven implementation intention and mental contrasting instructions (DDIIMC condition). Data-related elements of the planning tool (i.e., filters, calendar, and summary) only appeared when data use was part of the instructions (i.e., these elements were only shown for DDIIMC and DD conditions). If-then behavior plans were of the form “If ... (the obstacle or an opportunity to prevent it) arises, then I will do ... (actions in time, location, and other context) to overcome or prevent the obstacle.” For example, “If I get emails after work hours, then I will use the focus time app on my phone to auto-hide it.” Positive thinking plans were of the form “I want to ... (actions to take) to achieve my goal to ... (goal for improving work-nonwork balance)”. For example, “I want to finish coding by 3pm to work on administrative tasks to achieve my goal to finish all work-related activities by 5pm.”

Participants collected personal data during the first week of the study using the logging interface we had designed for active reporting of activities, locations, and progress toward goals (Section 3.1). They were then randomly assigned to one of the four conditions for creating behavior plans at the start of the second week of the study. They repeated the plan creation at the start of the third week. Our analysis and reporting are based on data from the third week; the main purpose of the second week was to acclimate participants to planning in a given condition and to reduce the impact of the novelty of the experience on the outcomes. It additionally allowed participants to adjust logging to their needs for the plan creation of the third week. We detail the steps of the study in Section 4.3. Participants were compensated with $175 Amazon gift cards for completing the study activities. They received an additional $75 gift card if they fully logged their activities for 18 of 21 days of the study. Our study was approved by our institution’s Institutional Review Board (IRB).

4.1 Participants

We reached out to a randomly sampled group of information workers at a global technology company where workers may collaborate across multiple timezones. Our recruitment email advertised the study as an investigation into different ways of improving work-nonwork balance using tools that allow users to create and protect time for activities that matter to them. It also included a brief screening survey, which we used to only enroll employees who resided in the US and were able to commit to the logistics of the study, those who met the technology requirements for participation, and those who were meeting the requirements for benefiting from the solutions we offered.

We screened respondents to our call to ensure participants were available for the duration of the study and anticipated that their schedules during the study would be representative of their typical schedules. The former requirement guaranteed the completion of study activities as planned, while the latter was important to control for extremes of overload (e.g., a major deadline) or underload (e.g., traveling or personal leave) as the study content and data were less relevant under these extremes. The primary technology requirement was to have the Microsoft Teams mobile application installed to allow participants to receive and engage with daily reminders during both working and nonworking hours.

We drew from behavior change literature to limit participation to people who report not having work-nonwork balance (i.e., they have recognized the problem area to address) and are in the preparation stage of change (i.e., they are *ready* for change but have not taken any actions yet). This group of people has the intent for change and can substantially benefit from support in doing so [88]. Support may be useful at later stages of change too but we scoped our research to this particular stage for experimental control purposes: we chose to focus on a stage of change where the affordances of our tools are well suited for addressing the known challenges, in the absence of evidence on whether and how our approach leads to improved outcomes. Behavior discovery (i.e., identifying the relevant actions to take) is a key but challenging step of the preparation stage [38] and our tool offers multiple avenues for addressing this challenge (see walk-through of Section 3.2.2 for details).

Our process led us to recruit 48 adult participants (12 per condition). From these, we removed 5 participants (2 in basic control, 1 in DD, and 2 in DDIIMC conditions) over the course of the study because of personal emergencies (e.g., travel due to family health concern) or low compliance. We report findings for the 43 remaining participants. Table 1 summarizes demographics for the study and across four study groups. Briefly, 22 identified as male, 21 as female (1 preferred not to identify their gender). 12 were 35 years and younger, while 30 were 36 years and above (1 participant did not provide their age). All participants who provided their education information (all but 1) had post-secondary degrees of which 20 also had a graduate degree. They occupied both management (21) and individual contributor (19) roles (3 did not provide roles).

Table 1. Demographics of Study Participants. Participant ID assignments in each condition are given in the last row and will be used in quoting participants.

	Total	Basic control	DD	IIMC	DDIIMC
Man	22	5	6	7	4
Woman	20	5	5	5	5
Unspecified Gender	1				1
18-25 years old	1			1	
26-35 years old	11	3	3	4	1
36-45 years old	13	4	2	5	2
46-55 years old	15	3	6	1	5
56-65 years old	2			1	1
Unspecified Age	1				1
Graduate degree	20	6	2	6	6
Post-Secondary degree	22	4	8	6	4
Unspecified Education	1		1		
Individual Contributor	19	6	2	4	7
Manager	21	4	6	8	3
Unspecified Job Role	3		3		
Range of Participant IDs	1-43	34-43	23-33	11-22	1-10

4.2 Measures

We collected information on the relevant outcomes along with factors that can affect the outcomes in addition to the experimental condition. We also collected information to verify the planning tool successfully supports a reflective process as the key mechanism of interest that underlies data-driven IIMC.

Addressing **RQ1** (if we improve understanding of obstacles and opportunities for action), we asked participants for ratings on whether the planning tool helped them:

(1) Find obstacles that get in the way of following their plans (obstacle identification)
(2) Find problematic behaviors in achieving their plans (problematic behavior identification)
(3) Identify opportunities for actions in the short-term, i.e., within a week (short-term action identification)
(4) Identify opportunities for actions in the long-term, i.e., beyond a week (long-term action identification)
(5) Identify opportunities for rescheduling plans (rescheduling ability)
(6) Become more aware of their adherence to plans (adherence awareness)
(7) Become more determined in adhering to their plans (adherence determination)

We obtained these ratings on a 5-point Likert scale (1: strongly disagree – 5: strongly agree) at the end of week 3 of the study as doing so earlier could have confounded the natural use of the planning tools (planning tools varied based on experimental condition; see further details in Section 4.3).

Addressing **RQ2** (if we can improve work-nonwork balance), we considered perceived work-nonwork balance and time-management at baseline (i.e., start of week 1 of the study) and exit (i.e., at the end of week 3 of the study). We asked participants to provide this information based on their experience over the prior week at each time point. Specifically, we obtained involvement, effectiveness, and affective balance subscales as measures of perceived work-nonwork balance [101]. We derived a measure of time-management from [76] as the sum of Likert ratings (1: Never – 5: Very Often) of the following statements: feeling pressed for time, managing time easily, keeping planned times (e.g., appointments, meetings, blocked time) easily. The first item was reverse-coded before obtaining the sum.

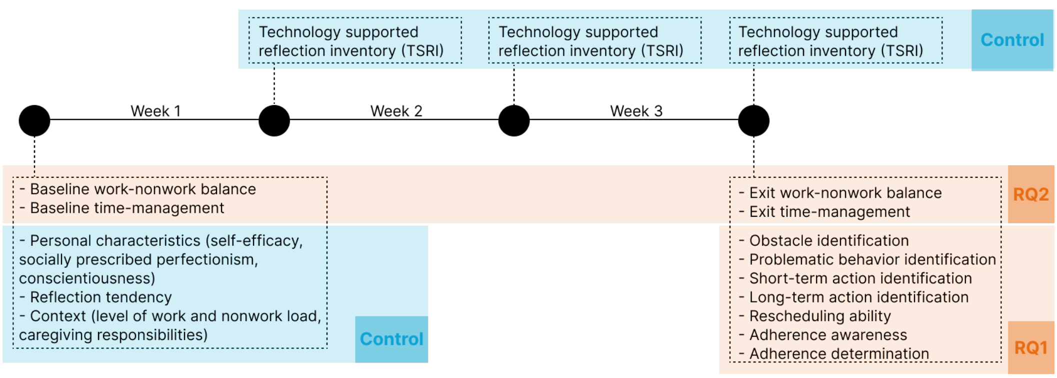

Fig. 9. Study Measurements. Measurements addressing **RQ1** were obtained at the end of week 3 of the study. Baseline and exit measurements of **RQ2** were obtained at the beginning and at the end of the study. Several control variables including personal characteristics, reflection tendency, and context were obtained at the beginning of the study. Weekly measures of planning and logging reflection were also obtained as control via insight subscale of technology supported reflection inventory (TSRI).

We obtained measurements for a number of factors that could influence the outcomes in addition to the experimental condition. Doing so allowed us to either establish that conditions were comparable with respect to a factor or to control for the effect of the factor in the comparisons. The factors we measured pertain to personal characteristics that impact the effectiveness of different aspects of data-driven IIMC, individual contexts, and activities. With respect to personal characteristics, we collected measures of self-efficacy [16], socially prescribed perfectionism [51], and conscientiousness [41] as past research has shown they influence the effectiveness of IIMC application. We also collected reflective tendencies [82] that can affect whether individuals are inclined to engage in a reflective process. We obtained these measures at the beginning of the study. With respect to individual context, we asked about levels of work and nonwork load as well as caregiving responsibilities and resources at study onboarding. With respect to individual activities, we obtained weekly measures of the insight subscale of technology-supported reflective inventory (TSRI-insight) [6] to measure the level of reflection associated with using the logging interface, as past research indicates the act of recording information is reflective in and of itself [103]. We consider the reports of TSRI-insight for the last week of logging as the most stable representation of reflection at logging.

We obtained a weekly measure of TSRI-insight with respect to the planning tool to verify that it successfully supported reflection and helped participants gain insights into achieving their work-nonwork goals. We use reports of reflection on planning tools in week 3 as the representation of planning reflection. Figure 9 details the measurements we obtained at different times in the study.

4.3 Procedure

Upon enrolling in the study, participants completed onboarding activities. They completed standard questionnaires on their perceived self-efficacy [16], socially prescribed perfectionism [51], conscientiousness [41], and reflective attitude [82]. They also responded to questions about their work and nonwork load as well as caregiving responsibilities and resources, described their views of the desired work-nonwork balance, and customized the list of activities and locations to log.

At the start of each week of the study, participants reported their perceived work-nonwork balance and time-management over the past week. They then reviewed their work-nonwork balance goals and the plans to achieve those goals, updated their goals as needed, and modified/refined their behavior plans except at the start of week 1, when they described work-nonwork goals and plans for the first time. All groups used the basic control tool for behavior planning of week 1 as a baseline. Starting at week 2, participants used their assigned tools for behavior planning at the start of the work week. That is, DDIIMC and DD groups used the planning tool in Figure 2 with respective instructions on the left per Figure 8, whereas IIMC and basic control groups received their respective instructions without having access to the visual elements of the planning tool (i.e., filters, calendar, or summary parts). We displayed each participant their description of the desired work-nonwork balance at the time of goal setting and behavior planning to ensure their ideals are available for consideration in decision-making. This strategy was an attempt to help participants come up with plans that were more relevant to them. Participants responded to TSRI-insight after using the planning tool.

During the week participants were reminded randomly five times a day during waking hours to log their activities, whereabouts, and progress. We asked participants to complete TSRI-insight with respect to the logging tool at the end of the week.

At the end of week 3 of the study, participants reported their perceived work-nonwork balance and time-management over the last week of the study. They then rated the statements that we specifically designed to address **RQ1** (see the details in Section 4.2). They also responded to open ended questions about their experience in the study. These questions asked about what they liked/disliked, how they used the tools, and ways we can improve them.

4.4 Analysis

We created regression models of the form $outcome \sim data + iimc + iimc \times data + control$ to address **RQ1**. We created a separate model for each measure of **RQ1** as *outcome*. We used *data* and *iimc* as binary variables that captured whether reflection on data and IIMC instructions were received. Therefore, both *data* and *iimc* were 1 for DDIIMC group, whereas they were both 0 for basic control group. Only *data* was 1 for DD group, while only *iimc* was 1 for IIMC group. We considered two categories of variables to select the *control* variables: (1) demographics (Table 1) as past research has shown differences in outcomes in relation to these characteristics [35, 46], and (2) personal characteristics as well as individual context and activities (see Section 4.2). We included as *control* variables those variables that differed among conditions or showed significant correlations with the outcome of interest. No demographic variables were included in the models as Fisher's exact test showed no significant differences across conditions on demographics (Fisher's test is preferred over χ^2 test over small samples). We included self-efficacy in the model of determination for plan adherence given their significant correlation. Similarly, we included conscientiousness in models for identification of obstacles and rescheduling opportunities. We controlled for levels of reflection at logging in all models as this variable was significantly correlated with all outcomes. Control variables included for each outcome are listed in Table 4. We used the *lm* function of `stats` package in `R` [89] to create the regression models.

Addressing **RQ2**, we used mixed ANOVA with time (baseline to exit) as the within factor and condition as the between factor to examine if mean changes in perceived work-nonwork balance subscales and time-management differ across conditions. We did a follow-up analysis on significant main effects when doing so was possible (i.e., there was no interaction effect between time and condition): dependent-sample t-test to follow up on the main effect of time and Tukey's HSD to follow up on the main effect of condition. We used the `rstatix` package [55] to test ANOVA assumptions and obtain test statistics for mixed ANOVA analysis and Tukey's HSD. We used the `stats` package for paired-sample t-test [89].

We took several steps in verifying various aspects of our methodology. First, we examined the relevance of the custom measures of **RQ1** to the work-nonwork balance construct by examining the correlations between these custom measures and the validated measure of perceived work-nonwork balance [101]. If correlated, we have evidence that the use of the planning tool has activated mechanisms intended by IIMC in the context of work-nonwork balance. Second, we used a one-sided t-test to compare week 3 measurements of TSRI-insight on planning tools with the mid score of 12 on this subscale for each study condition to check whether planning tools successfully supported reflection. This strengthens the assumption that reflection processes we assumed to be active are in fact active. We applied Bonferroni correction to the nominal α of 0.05 (i.e., we used p-value of 0.0125 to establish significance) to account for type I error of multiple comparisons.

We triangulated the quantitative analysis of our measures with the qualitative analysis of survey responses as the latter could contextualize quantitative patterns. Triangulation is commonly used in HCI as a way of obtaining a more "reliable, holistic and well-motivated understanding of phenomena" [83]. Our qualitative analysis drew upon reflexive thematic analysis methodology [11], where we considered comments in light of the outcomes we were examining quantitatively: the first author reviewed comments in relation to such objectives as change in awareness, planning process, or perceived improvements, while iteratively coding for additional nuances (e.g., factors influencing planning). Another author reviewed the first author's coding of comments. Coding disagreements were resolved through discussion.

5 RESULTS

We find that the planning tools which provide instructions within the framework of implementation intention and mental contrasting (IIMC) successfully guide reflection in behavior planning. We also observe the importance of data in combination with IIMC instructions for increased awareness of plan adherence and the ability for rescheduling, qualities that are important in realizing work-nonwork balance goals. Moreover, our observations indicate significant improvements in perceived work-nonwork balance and time-management across experimental conditions. We detail our findings in the following subsections. Our use of the word 'significant' in the reports means 'statistically significant'. We use the standard significance level of 0.05 unless adjustments were needed (see Section 4.4).

5.1 IIMC Instructions Guide Reflection in Behavior Planning

Comparing TSRI-insight scores for week 3 of planning across conditions, we find that DDIIMC and IIMC groups report levels of reflection that are significantly larger than the mid-point score of 12 on the TSRI-insight subscale for their assigned planning tool (DDIIMC mean=15.6 and IIMC mean=16.25; Table 2). We did not find statistically significant evidence that DD and basic control groups report levels of reflection above the mid-point threshold (DD mean=12.73, basic control mean=14.90). Figure 10 provides the distribution of scores across conditions. We repeated the analysis with a one-sided Wilcox signed rank test for DD and basic control groups given the non-normal distributions of scores for these conditions. We did not find significant evidence that the level of reflection in these groups surpasses the mid-point threshold.

Table 2. Descriptive statistics of TSRI-insight scores for week 3 of planning across conditions along with one-sided t-test comparisons against the mid-point score of 12. TSRI-insight values vary in the range of 3-21 (larger values indicate higher levels of reflection). The significance level is coded with stars (*: p < 0.05, **: p < 0.01).

Group	Mean	Std.	t-test	p
DDIIMC	15.60	3.69	3.09	**
IIMC	16.25	4.29	3.43	**
DD	12.73	5.20	0.46	
Basic control	14.90	4.95	1.85	

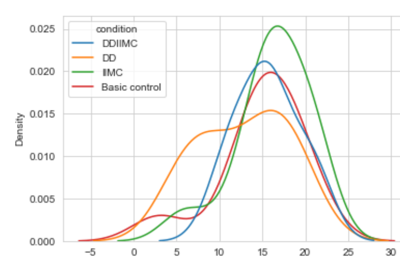

Fig. 10. Distribution of TSRI-insight Scores for Planning Interface in Week 3 for DDIIMC (blue), IIMC (green), DD (orange), and basic control (red) Conditions.

5.2 Increased Plan Awareness and Rescheduling for Work-Nonwork Balance in DDIIMC

Custom-defined measures of **RQ1** are significantly correlated with perceived work-nonwork balance subscales. Correlation coefficients are moderate to large (min = 0.32, max = 0.68; Table 3). We thus have evidence for the relevance of the measures and can more confidently interpret them.

We find affirmative support for **RQ1**. We observe significant differences across conditions for measures of rescheduling ability, adherence awareness, and adherence determination: participants in DDIIMC condition report significantly higher ratings for the value of their planning tool in enabling them to reschedule ($F(1)$=4.74, p=0.036) and to become more aware of their adherence to the plans they have for improving work-nonwork balance ($F(1)$=4.11, p=0.050). However, DD group's determination for adhering to their plans is significantly diminished compared to other

Table 3. Correlations Coefficients between Custom Measures of **RQ1** and Standard Measures of Work-Nonwork Balance [101]. The significance level is coded with stars (*: p < 0.05, **: p < 0.01).

	Involvement balance	Affective balance	Effectiveness balance
Obstacle identification	0.52 **	0.51 **	0.57 **
Problematic behavior identification	0.63 **	0.48 **	0.6 **
Short-term action identification	0.48 **	0.32 *	0.48 **
Long-term action identification	0.52 **	0.39 *	0.47 **
Rescheduling ability	0.4 **	0.52 **	0.45 **
Adherence awareness	0.47 **	0.52 **	0.55 **
Adherence determination	0.48 **	0.47 **	0.49 **

groups ($F(1)$=5.73, p=0.022). Table 4 lists the regression coefficients across input variables for different outcomes.

DDIIMC participants' survey responses qualitatively contextualized our observations above. Some participants explicitly attributed their increased awareness of their plan compliance to reviewing data. For example, P2 said *"I reviewed my study behavior plan and last week saw blocks where I did not follow the nonwork and work plan."* Similarly, P7 said she most liked *"the visibility into my own schedule and how closely (or not) I was able to stick to my calendar."* Describing her use of data toward rescheduling, P9 said *"I could see that there is time gaps in my day that allow me to think about moving my blocked time."*

We find that levels of reflection at logging (measured using weekly TRSI-insight scores) are significantly related to a better understanding of obstacles and opportunities: the more participants reflected at the time of logging, the more they could identify obstacles or problematic behavior when planning ($F(1) = 26.48, p \ll 0.001$). Similarly, they were better at finding opportunities for action in the short and long-term or options for rescheduling ($F(1) = 16.77$, 20.27, and 29.17, respectively, $p \ll 0.001$). Moreover, they felt more aware of their plan adherence and more determined in following through with their plans ($F(1) = 4.34$ and 32.67, respectively, $p < 0.044$). Conscientiousness significantly explained additional variations in identifying opportunities for rescheduling ($F(1) = 6.41, p = 0.016$).

The value of logging was also evident in participants' responses to open-ended survey questions. For example, P34 said *"Putting down all my tasks for the day and the time I did them allowed me to reflect on which areas I can improve on."* Or P24 said *"Having to log all my time was a real wake-up-call to how my week passed."*

In addition to an increased awareness and understanding of obstacles, we find that DDIIMC instructions (Figure 3) guided participants to create a concrete behavior plan that directly addressed

Table 4. Coefficients for Regression Models of **RQ1**. Outcomes appear on the rows. We report estimated coefficients for all input variables that were included for each outcome along with the standard error for the estimates in parenthesis (an empty cell means the variable was not part of the model). The range of values for logger reflection, self-efficacy, and conscientiousness are 3-21, 1-5, and 5-50 respectively. Larger values indicate higher levels of reflection, self-efficacy, and conscientiousness. Significance level is coded with stars (*: p < 0.05, **: p < 0.01, ***: p < 0.001).

	data	iimc	data × iimc	logger reflection	self-efficacy	conscientiousness
Obstacle identification	0.08 (0.36)	0.06 (0.36)	0.31 (0.51)	0.14*** (0.03)		0.04 (0.04)
Problematic behavior identification	0.48 (0.35)	0.43 (0.34)	-0.36 (0.49)	0.14*** (0.03)		
Short-term action identification	-0.07 (0.44)	-0.00 (0.43)	0.13 (0.62)	0.13*** (0.03)		
Long-term action identification	0.19 (0.33)	0.24 (0.32)	-0.05 (0.46)	0.11*** (0.02)		
Rescheduling ability	-0.45 (0.38)	0.23 (0.38)	1.16* (0.53)	0.15*** (0.03)		0.06* (0.03)
Adherence awareness	-0.80* (0.36)	-.0.57 (0.35)	1.02* (0.50)	0.06* (0.03)		
Adherence determination	-0.84* (0.35)	-0.24 (0.34)	0.84 (0.52)	0.15*** (0.03)	0.53 (0.31)	

the obstacle identified through data. For example, P3 was made aware that responding to emails after work hours was a norm, not an exception: *"I see that I was working from 8 pm to 9.30 pm last week from the app."* He then identified phone notifications as an obstacle: *"I get notifications on my phone when someone emails me on my work email. If it's important or interesting, I tend to answer those."* Finally, he created a behavior plan as if-then statements that addressed his observation: *"If I get emails after work hours, then I will use focus time app on my phone to auto-hide it to overcome or prevent the obstacle."*

5.3 Increased Perceived Work-Nonwork Balance and Time-Management during Study

Our data positively supports **RQ2** with respect to improvements in work-nonwork balance as we see enhanced measures over the study duration across all study conditions. However, there is no evidence that DDIIMC improvements are surpassing the alternatives. Mixed ANOVA models pertaining to **RQ2** indicate no significant interaction effect between time and condition. We can thus directly interpret the main effects. We find a significant main effect for time: participants more favorably rate their time-management at exit compared to baseline with average improvements of 1.84 over the range of 3 to 15 for this measure (Figure 11; $t(42) = 5.13, p \ll 0.001$). Moreover, participants report large to very large improvements in measures of perceived work-nonwork balance from baseline to exit. Specifically, affective, effectiveness, and involvement balance scores improve by 0.53, 0.55, and 0.98 on average over the range of 1 to 5 for these measures (Figure 12; $t(42) = 4.01, 4.08$, and 5.95, respectively, $p \ll 0.001$ for all).

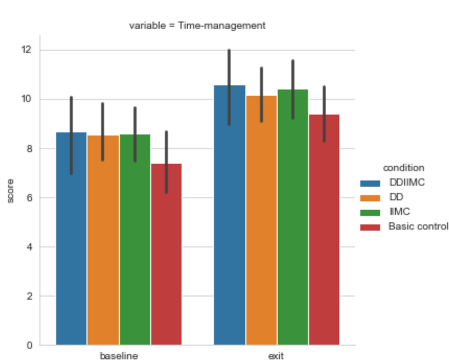

Fig. 11. Baseline and Exit Scores of Time-management. DDIIMC, DD, IIMC and basic control conditions are color-coded by blue, orange, green, and red respectively. Error bars indicate a 95% confidence interval based on group standard deviations. There is a very large but condition-agnostic improvement.

However, there is no significant main effect for condition: the average change over time does not differ across conditions – work-nonwork balance and time-management similarly improved for all conditions, independent of the planning interface they used over the course of the study. Table 5 provides descriptive and test statistics for the measures.

Qualitative survey responses corroborated the observed improvements in work-nonwork balance and time-management. They also brought to light important nuances in the multi-stakeholder context of work and nonwork. P18 explicitly connected improvements in work-nonwork balance to their participation: *"The exercise helped me prioritize my non-work activities in my day-to-day life and achieve better balance"*. P37 made a similar comment, while acknowledging the tension between work and nonwork and her agency in making choices and acting on them: *"This process made me very mindful of work and nonwork times and [I] was more deliberate about my choices (when I had choice) [to] step away both in the mornings to quickly check my messages or the evenings to get one last thing out the door, and many times I do have the choice but not every time."*

Some participants described the realization of the role of external influence in their work-nonwork balance as the most helpful aspect of their participation, confirming that work-nonwork balance does not pertain only to the individual but the people and work context around them [10]: *"Recognition that I don't have as much agency in what makes me busy at work. I'm at the whims*

Table 5. Descriptive and F Statistics for Variables of **RQ2**. Subscales of perceived work-nonwork balance vary in the 1-5 range. Time-management scores are in the range of 3-15. Larger values indicate better work-nonwork balance and time-management.

	Affective balance				**Effectiveness balance**				**Involvement balance**				**Time-management**			
	Baseline		**Exit**		**Baseline**		**Exit**		**Baseline**		**Exit**		**Baseline**		**Exit**	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
DDIIMC	3.52	0.71	4.24	0.69	3.54	0.71	4.26	0.68	3.43	0.57	3.87	1.26	8.7	2.67	10.6	2.55
IIMC	3.4	0.64	3.95	0.59	3.5	0.71	4.03	0.45	2.94	0.99	3.56	0.74	8.58	1.98	10.4	2.11
DD	3.58	0.49	3.8	1.07	3.73	0.53	4.13	0.87	3.48	1.1	4.03	0.69	8.54	2.02	10.2	2.04
Basic control	3.36	0.43	4.02	0.43	3.48	0.56	4.04	0.42	3.4	0.84	4.07	0.61	7.4	2.12	9.4	1.84
$F_{condition}(3,39)$	$0.40, p = 0.76$				$0.43, p = 0.74$				$1.27, p = 0.3$				$1, p = 0.4$			

of other people's calendar and requests that can disrupt my best laid plans. This is likely driven from my desire for impact, recognition, and eventually promotion but the questions prompted during this study really surfaced this" (P40). Some took this recognition to action and wanted to share their data-backed insights with others (peers, managers, family members) to mitigate the external demands. P4 suggested *"a way to collaborate with your life partner / spouse if you are sharing home responsibilities"* as the main improvement to the tool.

Condition-independent improvements despite the differences in planning-related measures of **RQ1** suggest that a factor other than planning drives the improvements in perceived work-nonwork balance and time-management. To further examine the factors that influence the changes in perceived work-nonwork balance and time-management, we built regression models of the form $\Delta outcome \sim data + iimc + data \times iimc + other$. $\Delta outcome$ is the difference in exit with respect to baseline for $outcome$ scores; $data$ and $iimc$ were defined similar to regression models of **RQ1**. Similarly, $other$ was selected from personal characteristics or individual activities (i.e., logging) variables based on whether these variables were significantly correlated with the outcomes. The selections were: self-efficacy for all subscales of perceived work-nonwork balance, conscientiousness for all subscales but the involvement balance, and levels of reflection at logging for all measures of perceived work-nonwork balance and time-management.

Reflection at logging turned out to be a significant predictor of change in all work-nonwork balance and time-management outcomes ($F(1) = 12.96, 9.41, 5.47$, and 8.01 for time-management, affective, effectiveness, and involvement balance, respectively, all $p < 0.025$), similar to earlier

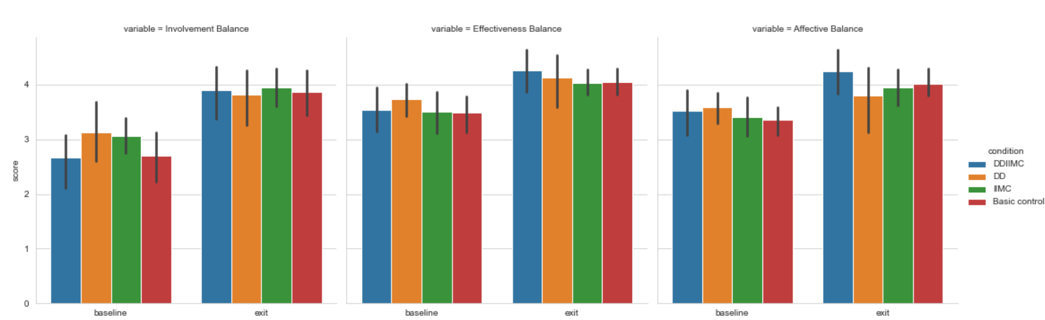

Fig. 12. Baseline and Exit Scores of Perceived Work-Nonwork Balance. From left to right, we have involvement balance, effectiveness balance, and affective balance. DDIIMC, DD, IIMC and basic control conditions are color-coded by blue, orange, green, and red respectively. Error bars indicate a 95% confidence interval based on group standard deviations. There are large to very large improvements across all subscales of perceived work-nonwork balance but the improvements are not condition dependent.

Table 6. Coefficients for Regression Models of **RQ2**. Outcomes appear on the rows. Δ is the change from baseline to exit. We report estimated coefficients for all input variables that were included for each outcome along with the standard error for the estimates in parenthesis (an empty cell means the variable was not part of the model). The range of values for logger reflection, self-efficacy, and conscientiousness are 3-21, 1-5, and 5-50 respectively. Larger values indicate higher levels of reflection, self-efficacy, and conscientiousness. Significance level is coded with stars (*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$).

	data	iimc	data × iimc	logger reflection	self-efficacy	conscientiousness
Δ Affective balance	-20.3 (0.36)	-0.19 (0.36)	0.36 (0.52)	0.08** (0.03)	0.34 (0.32)	0.00 (0.03)
Δ Effectiveness balance	-1.11 (0.39)	-0.10 (0.38)	0.27 (0.57)	0.07* (0.03)	0.03 (0.35)	0.02 (0.03)
Δ Involvement balance	-0.43 (0.45)	-0.34 (0.44)	0.64 (0.67)	0.09** (0.03)	0.22 (0.40)	
Δ Time-management	-0.38 (0.93)	-0.27 (0.91)	0.28 (1.30)	0.25*** (0.07)		

observations that it was significantly related to plan awareness and rescheduling. Self-efficacy and conscientiousness did not significantly explain variations in any of their respective models (Table 6). Despite the benefits of enabling reflection and prioritizing work-nonwork balance, participants also hinted at the burden of data collection. For example, P29 said *"I like the daily reminders although logging time does cause some stress to get it done. That said, the reminders that come in Teams remind me to make this (referring to her nonwork goal) a priority."*

6 DISCUSSION

We examined whether reflection on personal data can help decision-making in creating behavior plans for improving work-nonwork balance and chose to use the implementation intention and mental contrasting (IIMC) framework to explore our research questions. Our results demonstrate the value of data in an IIMC-based planning tool. More importantly, they highlight additional opportunities for supporting decision-making with data and thereby enabling more effective application of IIMC and other similar techniques. Furthermore, we found that reflection helped participants become more aware of their agency under external forces in the multi-stakeholder context of work and nonwork, where data can play a boundary-negotiating role [21]. Although our study is in the context of work-nonwork balance, several findings and their implications have broader applicability which we further discuss below. In the following subsections, we more closely interpret our results, discuss the opportunities for further supporting IIMC with data, share ideas for bringing IIMC to the workplace, and critically examine the limitations of our work.

6.1 Data Complements IIMC in Planning but There is More to Goal Realization

We observed increased subjective awareness of adherence to goals and capability for rescheduling plans among DDIIMC participants in our study (Section 5.2). These observations provide evidence that the review of personal data leads to insights that can help with creating IIMC-based behavior plans for improving work-nonwork balance. That is, our study shows that reflection on data complements IIMC approaches. We additionally observe that IIMC instructions scaffold and facilitate reflection. We note that planning reflection levels for DDIIMC and IIMC groups surpassed the mid-point threshold while the same did not happen for DD and basic control groups (Section 5.1). The case for DD is particularly interesting. In the absence of guidance when reviewing data there is no gain but loss: participants in DD report diminished determination in following their plans (Section 5.2). This can be explained through the interrelation between motivation and IIMC [75]. Reviewing data likely brought to light the gap between the desired and actual state of work-nonwork balance. This realization subsequently undermined participant determination as there was no guidance on addressing the gap. Our study shows that the IIMC technique explicitly supports people in overcoming the gap, though there may be other tools that do this as well.

We also found condition-independent improvements in perceived work-nonwork and time-management from baseline to exit (Section 5.3). Study procedures involved multiple behavior change techniques including goal-setting, tracking (in the form of logging), and behavior planning. While we isolated and varied the latter only, other techniques could drive the improvements individually or in combination with the rest. We showed that reflection associated with logging was a significant predictor of improvements above and beyond planning (Section 5.3).

6.2 Micro-Reflection on Data in Recent Past Can Support IIMC Plan Formation

Observations of increased rescheduling ability and adherence awareness without loss in adherence determination in Section 5.2 demonstrate the importance of guided *macro-reflection* where people review their personal data to identify opportunities for action within the IIMC framework. However, such macro-reflection was not the only source of benefits for our participants. Logging data and reflecting on one's behavior when doing so were key to success in planning-related activities (Section 5.2) as well as improvements in perceived work-nonwork balance and time-management (Section 5.3). These observations are consistent with other reports, e.g., [19, 63], which similarly found reflection happens at the time of logging. In our setting, reflection at logging is a form of *micro-reflection* where people pay attention to their behaviors in the very recent past and within a short window of time when logging. In doing so, they notice divergence from desired behaviors, the underlying reasons (i.e., obstacles), and potential solutions. This is evident in the significant positive relations between levels of reflection at logging and ratings of the ability to identify obstacles, problematic behaviors, and opportunities for action (Section 5.2). It is noteworthy that macro-reflection on data when planning did not seem to explain these outcomes; the DDIIMC group did no better than the others. Not surprisingly, micro-reflection at logging also showed the importance for rescheduling and awareness of plan adherence and thus complemented macro-reflection at DDIIMC planning (Section 5.2). In light of these results, we call out for attention to and investment in leveraging micro-reflection for IIMC. The ideas and lessons from research on just-in-time adaptive interventions can be leveraged, e.g., in determining the number, timing, and content of micro-reflection prompts [64, 65, 72, 73].

We contrast our position with much of the past HCI research on implementation intentions, which has focused on the *automatic detection of identified situations* for triggering action (e.g., [8, 85]). Contrary to previous work, we emphasize micro-reflections through *low-cost and simple logging for identifying situations*. Our results provide evidence for the value of leveraging data with this approach alone and in combination with the review of personal data. When combined in support of IIMC, micro-reflection helps people at forming the *'if'* part of if-then plans by boosting their ability to identify the relevant situations. Macro-reflections then support the *'then'* part of if-then plans when people decide on the specifics of actions to take.

6.3 Incorporate Data-Driven IIMC in Existing and Future Workplace Tools

Our results indicate the value of incorporating data-driven IIMC in workplace well-being context through both micro- and macro-reflection techniques. There are several possibilities for supporting these techniques. With respect to micro-reflection, the simplest practical implementation can use fixed reminders employees set for themselves to think back on their activities, whether those activities align with their work-nonwork balance goals, reasons for divergence, and ways to overcome or prevent it. This is similar to the reflection feature of such apps as Viva[1] but underscores explicit scaffolding of the reflective process. Moreover, calendar or meeting/communication applications can prompt quick reflection on how well the time was spent after each scheduled block of time or

[1]https://learn.microsoft.com/en-us/viva/insights/personal/teams/viva-insights-reflect

bout of communication. Predicting opportune moments for micro-reflection can further empower employees to more easily integrate micro-reflection in their day-to-day work (e.g., predicting moments of transition or break similar to [57] or when the chances of engagement are high as in [84]). However, this is a delicate design space as competing factors may complicate micro-reflection at opportune moments as noted in other research [61] (e.g., momentary negative affect from micro-reflection can adversely influence engagement).

With respect to supporting macro-reflection, the simplest and most available solution for employees is to designate a time to review their calendars, clarify their goals, reflect on existing obstacles and problematic behaviors, and identify opportunities for action. There is already evidence for productivity and well-being benefits of reflective goal-setting [71]. Our emphasis is on the value of data and IIMC instructions in guiding the reflective process, and we specifically advocate for extending the same strategy to both work and nonwork goals. We acknowledge that standard calendar data may not be as rich as the kind of data underlying our findings. Nonetheless, it may be a useful resource and should be studied within a larger inquiry into the minimum requirements for the level of detail, coverage, and granularity (e.g., 30-minute vs. hour-long intervals) of personal data for meaningfully supporting IIMC. In another approach, it is possible to bring some personalized automation to the process where a system such as Pearl [53] can assist in the sense-making process of personal data to help identify potential obstacles and opportunities for action as employees define relevant concepts for the system to help them more closely analyze their behaviors. This approach heavily relies on the availability of telemetry and other passively-sensed data to employees, although we acknowledge that there are important privacy and ethical concerns with such data that should be separately addressed. It is best to combine micro- and macro-reflection, independently of the specifics of implementations of each.

The focus of our exploratory experiment was on improving individual-level decision-making and action toward bettering work-nonwork balance. However, it is too simplistic to assume work-nonwork balance, or any other workplace well-being topic is individually scoped. Obstacles may be driven by external factors. There might be a need for communicating and coordinating actions with others (e.g., direct reports, peers, supervisors, or family members). Personal data and IIMC-related insights can act as boundary-negotiating artifacts in navigating, communicating, and coordinating with others, albeit there are nuances around potentially conflicting employee vs. organization goals as well as power dynamics. Future research should closely examine DDIIMC within a group context. More broadly, it is important to explore ways IIMC-guided reflection on personal data can support change at the organizational and social level. The increased awareness and recognition of external factors that result from the reflection can be key ingredients of individual's agency for change, as we observed among participants who started conversations with their managers (Section 5.3).

6.4 Limitations

Our study relied on rich but manually logged activity, location, and progress information. Such data cannot be assumed in any practical setting. While this assumption helped narrow down the confounding factors, it is important to reproduce our results with more realistic data, such as calendar information or automatically sensed data using all-purpose or personalized detectors. As we later found, logging was a critical contributor to the improvements we observed. Reproducing our study with passively-sensed data can further tease apart the specific value of data in planning. We considered three sources of information but our analysis did not allow us to examine the relative importance of these different sources for the effects we observed. Moreover, we did not collect information on any additional sources of data participants might have found useful. We cannot thus speak to specific data requirements for a system such as ours. Our analysis primarily relied on subjective self-reports given the difficulties in defining generic objective measures of success for short-term goal realization across a variety of goals that our participants defined over the course of the study. We also note that our study was a field-deployment and we did not have control over participants' interactions with our tools and whether they leveraged other interfaces. For example, we could not prevent basic control or IIMC groups from consulting with their calendar as they were creating their behavior plans even though we assumed participants in these conditions did not rely on data. We restricted participation to people in the preparation stage of behavior change. Future work can study whether data review can complement IIMC in other stages of change.

7 CONCLUSION

Realizing work-nonwork balance goals is crucial for individual well-being as well as organizational success. As technologies become more ubiquitous in our lives, the same technologies that are designed to promote collaboration and foster connection at work and at home have impaired our ability to maintain a healthy work-nonwork balance. To help employees navigate the challenges of achieving their work-nonwork balance goals, we introduced data-driven implementation intention and mental contrasting (IIMC) that leverages reflection on personal data and IIMC instruction to guide the identification of not only the obstacles on the way of achieving work-nonwork balance, but also opportunities to address them. Our three-week evaluation of a system that facilitates this strategy showed improvements in measures of work-nonwork balance. Moreover, data-driven IIMC improved awareness of behavior plan compliance and rescheduling, which pertain to the pursuit of work-nonwork balance goals. We also observe the value of micro-reflection for IIMC, which must be carefully balanced with automated approaches to data collection. Our study expands the role of data-driven IIMC as a self-regulation technique to one that can be leveraged to initiate conversations with those that influence one's work-nonwork balance goal realization (e.g., manager, spouse). Future work should strive to understand the long-term impacts of data-driven IIMC on the individual as well as organizational outcomes.

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