Lessons Learned for Data-Driven Implementation Intentions with Mental Contrasting

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ABSTRACT

Goal setting and realization are important but challenging. These challenges can be mitigated through effective application of behavior change realization techniques such as implementation intention and mental contrasting (IIMC). IIMC relies on identifying situations compromising desired behavior (i.e., obstacles) and creating action plans to handle those situations (i.e., identifying what, when, and where of actions to prevent or overcome the obstacles). We explore ways historical personal data can enhance the efficacy of IIMC application in the context of improving work-nonwork balance in a probing study with 16 information workers at a large technology company. We share lessons learned from this study that can help designers in further supporting goal realization with data, guide researchers interested in more formal studies of IIMC, and point the research community to important areas of future work on data-driven IIMC, particularly in the work context (e.g., the social dimensions of sense-making and planning).

KEYWORDS

Implementation Intention, Mental Contrasting, Goal-Setting, Behavior Change, Work-Nonwork Balance, Reflection, Personal Data

ACM Reference Format:
Yasaman S. Sefidgar, Matthew Jörke, Jina Suh, Koustuv Saha, Shamsi Iqbal, Gonzalo Ramos, and Mary Czerwinski. 2023. Lessons Learned for Data-Driven Implementation Intentions with Mental Contrasting. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems (CHI EA '23), April 23–28, 2023, Hamburg, Germany*. ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3544549.3573851

CHI EA '23, April 23–28, 2023, Hamburg, Germany

ACM ISBN 978-1-4503-9422-2/23/04.
https://doi.org/10.1145/3544549.3573851

1 INTRODUCTION AND RELATED WORK

Goal setting and realization are crucial for successful behavior change [19], yet many people struggle and face challenges in starting to act, staying on track, and adjusting their efforts and resources [11]. Prior research has demonstrated that goal setting and realization can be improved through implementation intention (II) and mental contrasting (MC), two self-regulation techniques of goal pursuit that help individuals translate their intents to actions [13]. 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"). Once the connection is formed, people can perform the actions quickly and effortlessly when critical situations arise without going through the cognitively costly process of forming conscious intent and deciding the course of action [11]. MC asks people to elaborate on their desired state and identify the obstacles standing in the way of realizing that state. Clarifying the desired state provides a direction for action. If this desired state is perceived as feasible, contrasting with reality can strengthen the goal pursuit motivation [13], a determinant of successful behavior change [12]. II and MC have been successfully used for behavior change in a variety of settings, including health [7, 18], education [2, 9], and interpersonal problems [10, 15]. When combined, they form a powerful technique for realizing behavior change with effects that can surpass the separate effects of each [13].

Successfully applying implementation intention and mental contrasting (IIMC) requires people to identify *their own* obstacles and decide on actions doable *for them* via MC to then use these in *if* and *then* parts of II respectively [13]. Both tasks are non-trivial and are often carefully designed in narrowly targeted interventions, e.g., on changing food choices, snacking habits, smoking, or physical activity [18]. There is already evidence that people need support to recall specifics of deviations in expected behaviors [5] as well as failures in following planned behaviors [20], activities that underlie the application of IIMC. How can we address the challenges in performing IIMC-related activities and, subsequently, better the application of IIMC?

Relevant prior HCI research has been primarily focused on improving II, either by enhancing automaticity via reminders or recommending automatically generated II plans based on personal data. For example, Pinder et al. [17] 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. [4] explore the use of peripheral reminders to increase physical activity by enhancing the activation of goal-directed actions. Modeling daily routines, Dogangün et al. [8] automatically identify and recommend timeslots or situations that can be used as critical conditions in IIs for physical activity. However, past research has not explored scaffolding people's ability in creating relevant IIMC statements. Given that reflection on personal data has shown promise in increasing awareness of one's behaviors and context [6, 20], it can potentially improve the identification of personally relevant obstacles and doable actions to address them. Therefore, it is worth examining if reflection on personal data can support the application of IIMC.

In this case study, we report our work on enabling IIMC via *reflections on personal data*. In doing so, we built a reflection tool as a probe to further our understanding of the requirements and opportunities for data-driven IIMC. We situate this work in the context of improving work-nonwork balance in the workplace context where IIMC can be particularly useful [16]. Reflecting on our experience, including the challenges, various workarounds, and observations, we share lessons we learned that are applicable to (1) the design of data-driven IIMC tools, (2) the design of empirical studies more formally examining the efficacy and underlying mechanism of data-driven IIMC, and (3) areas of future research. In the following sections, we first describe the data collection and reflection tools we built for our work (Section 2) as well as the probing study (Section 3) where we put these tools into use. We then present and discuss our learnings in Section 4, go over the limitations of our work in Section 5, and conclude in Section 6.

2 BRINGING DATA TO IMPLEMENTATION INTENTION WITH MENTAL CONTRASTING

Our goal is to leverage personal data in applying implementation intention and mental contrasting (IIMC) in the context of improving work-nonwork balance. Specifically, we aim to support people to reflect on their personal data to identify not only obstacles that hinder their desired work-nonwork balance but also opportunities to prevent or overcome those obstacles. To understand the requirements and opportunities for the types and granularity of data to collect and the tasks to support with the data, we prototype a system that participants can use for IIMC-related activities above. The system consists of (1) a data collection tool (Section 2.1) that obtains data on activities, whereabouts, and progress toward work-nonwork balance plans and (2) a reflection tool (Section 2.2) that facilitates reviewing of the data within IIMC framework.

2.1 Data Collection

There are multiple approaches to obtaining data on activities, whereabouts, and progress. These range from fully manual reporting to

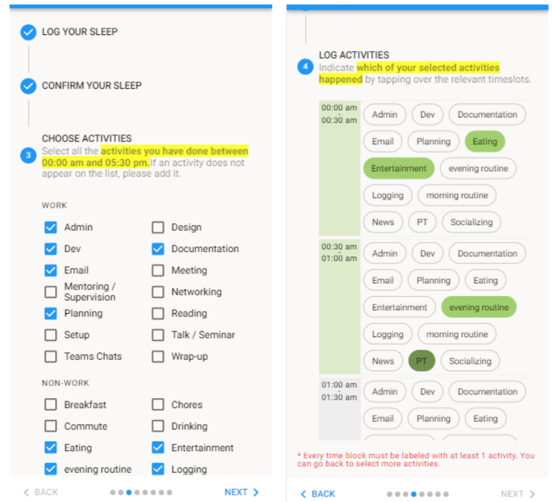

Figure 1: Data Collection Interface. Participants selected the activities they engaged in within the specific time window (midnight to 5:30pm in the example) from a customized list of activities (left image). They then marked the activities that happened during each 30-minute time slot (right image).

fully automated detection, to a mix of both. Being in the early stages of figuring out the data requirements, we chose manual reporting. More concretely, we sent five daily reminders to the interface shown in Figure 1 and asked users to enter data over 30-minute time slots for the past 3-4 hours and covering all 24 hours of each day. Users entered their activities, whereabouts, and whether the activities they engaged in were aligned with their work-nonwork balance plans which they specified at the beginning of the week. The tool supported entering custom activities and locations.

2.2 Reflection Tool

We built the tool shown in Figure 2 to guide users through a process where they could examine their activities, whereabouts, and progress to decide on the actions to take, when, and where within IIMC framework. Instructions appeared on the leftmost section and guided the reflective process consistent with IIMC steps (e.g., similar to [14]; Figure 2-a). Different views of data were available through filters on the right-most section. For example, Figure 2-b demonstrates view of work vs. nonwork. We also provided views of specific activities or locations as well as view of alignment/violation of activities with respect to work-nonwork balance plans. A calendar view in the middle showed time slots colored based on the data being presented (Figure 2-c). For example, a purple slot represents work-related activities and a green slot represents nonwork-related activities under work vs. nonwork filter. Additional details were available upon hovering over the slots, including locations and specific activities reported for the slot. The tool displayed aggregate summary information below the calendar (Figure 2-d). There were multiple forms of summary: (1) a 7-day trend showing weekly total and average hours of activities along with a color spectrum where the darkness varied by the length of time spent on the activity (the

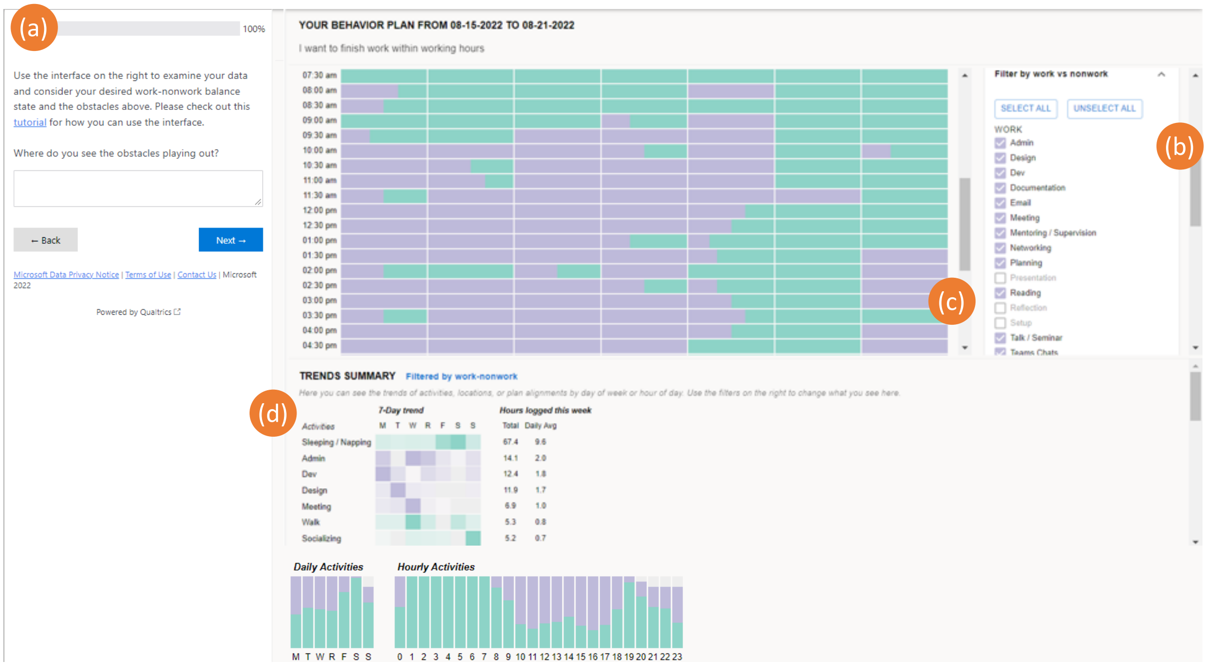

Figure 2: Reflection Tool Interface. (a) IIMC instructions were given on the left. (b) Participants could choose one of work vs. nonwork, activity, location, or plan alignment filters to get different views of their data. (c) The calendar in the middle displayed data of interest across days of the week and times of day. In work vs. nonwork view, purple represents work while green represents 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.

longer the time, the darker the color), (2) a daily activity graph showing activity breakdown on each weekday, and (3) an hourly activity graph showing activity breakdown over different times of the day. Drawing from past work on reflection design patterns [3], we included different data views in calendar and aggregate forms to help users explore how and where they spend their time, subsequently examine if their current behaviors matched their desired behaviors, and explore mismatches as well as opportunities to address them. An example task that could be achieved using the interface was to check working days and hours by either examining the distribution of purple slots over the calendar or reviewing daily and hourly breakdowns (i.e., larger purple segments appear on workdays and during work hours). This could quickly reveal if work is happening on undesired times and days.

3 EXPLORATORY STUDY

We conducted a study to explore how reflection on historical personal data can be used in forming IIMC behavior plans and to further our understanding of needs and opportunities in this space. To this end, we recruited 16 participants from a large technology company in Summer 2022 for a study on a tool they could use to gain insights to improve their work-nonwork balance. Participants were full-time employees working in a hybrid setting where they could work at the office or from home. Ten participants identified as men, five identified as women, and one preferred not to identify their gender. Eight participants reported as being 46-55 years old, four reported as being 36-45 years old, there was one participant in each of the 18-25, 26-35, and 56-65 year-old age groups, and one did not specify their age. Occupational roles of our participants included Program Manager (6 participants), Business Manager (3), Cloud Solution Architect (2), Technology Strategist (1), Data Scientist (1), Designer (1), and Developer (1), and one participant did not specify their role. Participants had a range of care-giving duties from definitely performing as the primary care-giver (7), to probably performing as one (2), to probably not performing as one (2), to definitely not performing as one (5). Participant who definitely or probably had care-giving duties had also scheduled support during working hours to be able to focus on work. Participants collected personal information using our data collection interface (Section 2.1) and used the reflection tool (Section 2.2) between one and three weeks. We first asked them to describe their desired state of work-nonwork balance and to come up with a specific, measurable, achievable, relevant, and time-bound (i.e., SMART) goal to achieve this state. After at least one week of data collection, we gave participants instructions to use our reflection tool and examine their data to better understand their behaviors, identify obstacles, and look for opportunities for actions that they could take over the next week or two to overcome or prevent obstacles. We then asked participants about their experience creating and following behavior plans in a follow-up, 30-minute, semi-structured interview. The interview session also involved a walk-through of participants' tool use where we briefly observed their interactions with the reflection tool. Below, we describe the lessons learned from these interviews.

4 LESSONS FROM AN EXPLORATORY STUDY

We first present practical lessons that can be immediately implemented by designers and developers of tools that support data-driven goal realization (Section 4.1). Then, we present recommendations for researchers interested in designing studies involving data-driven IIMC (Section 4.2). Lastly, we define future research opportunities to better understand the design and role of data-driven IIMC (Section 4.3).

4.1 Lessons on Design and Deployment of Tools for Data-Driven Goal Realization

We present five practical recommendations to consider during the design of data-driven goal realization tools. The first two recommendations are most useful in designing such tools within IIMC framework. The remaining recommendations are more broadly applicable to bringing data into the behavior planning process.

4.1.1 Support Answering 'Reflective Questions'. Our initial design of the reflection tool enabled obtaining information from data that pertained to basic questions such as 'what did I do, when, and where?' and 'did I follow the plan to achieve my goal?'. This was intentional, as we did not know what information people may want to draw from their data within the IIMC framework in the context of improving work-nonwork balance. However, such knowledge is important for the design of data-driven reflection tools, as they should allow users to get relevant information from their data. By observing participant interactions with their data and our tool, we identified additional information they wanted to get through reflection in the context of work-nonwork balance. We list these additional information needs as *reflective questions* that should be supported in this context. Supporting these questions should be considered as the design objective for future reflection tools for improving work-nonwork balance.

- What changes need to be made to my activities so that they are better aligned with my priorities and values?
  - Do I spend time on work during work hours and on nonwork during nonwork hours? More broadly, when (i.e., what times of day and what days of the week) do I spend time on different activities?
  - How much time do I spend on different activities or different types of activities (e.g., work vs. nonwork)?
  - Do I spend most of my time on my most valued tasks / priorities? If not, why and by how much do I diverge?
  - What are better ways for spending time?
- What changes need to be made to my activities so that I can be more effective?
  - When am I multitasking or attending to too many things within a short span of time?
  - Do I frequently context-switch? If so, why and by how much? How is my productivity affected?
  - Why are some days better (more productive, more energetic, etc.)?
- When is a good time for a certain activity (e.g., to match my levels of energy)?

4.1.2 Support Sharing with Others. The primary objective of our design was to create behavior plans within IIMC, i.e., to help people come up with actions they could *individually* take to avoid or prevent obstacles that get in the way of achieving their work-nonwork balance goals. However, multiple participants expressed their desire to take the insights they gained from our tool to have conversations with their managers and team members to more successfully manage the *externally* influenced obstacles. One participant was surprised that he had spent 25 hours in meetings over a week and said he would talk with his manager to decide on which meetings he should cut. The ability to share insights with others is thus an important feature to support. As we note below (Section 4.3.3) additional research should inform the design of this feature.

4.1.3 Incorporate Different Views of Data. Our tool provided different ways of filtering data (e.g., by work vs. nonwork or by activity) and viewing the filtered data (e.g., in calendar view or hourly / daily summary view). In our study, we observed that different filters and views not only enabled participants to answer different questions but also supported different ways of answering the same questions. For example, some participants appreciated the data summaries, but found the calendar view "too crowded" when examining their working hours. They looked at the hourly activities graph under work-nonwork filter to check after-hour work (i.e., purple segments after their typical end of the workday). Others found the calendar view to be the most useful for this question, as it allowed them to get a sense of their data quickly and easily (e.g., by checking if there are any purple slots after their typical end of the workday). Based on these observations, we recommend support for flexible data exploration over fixed, one-size-fits-all exploration alternatives.

4.1.4 Consider the Value of Active Reporting. We chose manual data collection as a reasonable choice for the exploratory purpose of our work despite its high burden on participants. While they acknowledged the burden, most participants also gained value from the manual entry of their data. Likening it to "diet tracking", they described how the manual entry made them more aware of their choices and priorities. Most participants found five times a day entry of all activities and locations to be excessive but were open to and infact, interested in, limited data entry (e.g., once a day and a lightweight report of energy, stress, or some other data of interest).

4.1.5 Make the 'Existing' Tools to be More Reflective. We provided our tool as a standalone web application. While participants appreciated the functionality it offered, they preferred to see it integrated into some of the tools they already used for two reasons. First, participants did not want to add another tool to the set of tools they already used. Second, they were more likely to use the functionality if it could easily become part of their existing workflow. Below is the list of some of their suggestions for ways a tool such as ours can be integrated in and further enrich the use of their familiar tools:

Calendar Annotations. Many participants wanted to add information to workdays or to specific blocks of time on their calendars for further reflection. Noting the close parallel between the temporal organization of data within our tool and their existing calendar apps, they said it would have been much easier for them to enter information on their productivity, energy levels, progress toward goals, etc. over the blocks of time in their calendar.

Protected Time for Work and Nonwork. Participants appreciated the ability to schedule focus time for work productivity tools and wanted to extend this functionality to nonwork goals, which would allow them to carve out time for their nonwork activities. They noted the importance of certain nonwork activities (e.g., exercise) for their productivity and wanted productivity tools to recognize this need and support them.

Budgeting Time. Several participants expressed interest in making time for specific projects. They found the ability to book focus time with their productivity tools very useful and wanted a more granular version of it to help them schedule time for specific projects based on their desired budgeting of time across projects.

Mixed Initiative Support. Although participants valued having agency over the data-driven planning process (e.g., the ability to choose the information being considered), they were also interested in computational support that augmented their agency. One participant wanted to set up their calendar to get recommendations on meeting slots that were spaced out after she realized that back-to-back meetings interfered with her nonwork priorities by draining her energy. Another participant wanted his calendar to take into account his energy level in suggesting meeting times based on automatically extracting his energy patterns.

4.2 Lessons for Future Studies on Data-Driven Implementation Intention with Mental Contrasting

We present two study design recommendations for researchers who are interested in further studying data-driven IIMC.

4.2.1 Allow Time for People to Tune In. Participants who used the reflection tool (Section 2.2) for three weeks described adjustments to the data they recorded and its use, particularly after the first week. For example, one participant mentioned that he did not find it necessary to mark activities as aligning with or violating their plan. After reviewing the data from the first week, he understood the role of that data and thus started marking whether activities were in alignment or violation of their plan during subsequent weeks. Participants who used the reflection tool only once wished they could change some of the information they recorded to get more value from the tool. It is thus very important to allow participants time to get used to the tool and adjust it in any study of the tool to control for the learning effect. We thus recommend at least two weeks of tool use, although it is common for similar IIMC studies to last only for a week [14].

4.2.2 Consider Short and Long-Term Behavior Change for Individuals and Groups. Participants described different ways in which they obtained value by examining their data within the IIMC framework, which is instructive in the further study of the topic. First, participants explained that they not only made immediate day-to-day improvements based on the insights they obtained from data (e.g., changes in meeting schedules) but also had plans for longer-term changes that typically required coordination with their managers or team members (e.g., changes to the projects they focused on). Second, most participants commented on finding the tool useful in increasing awareness of their behavior and opportunities to address the problematic ones. One person noticed how it was a norm rather than an exception for him to spend time on email after work hours. Another person noticed that back-to-back meetings got in the way of exercising and was able to identify hours of the day she was more likely to succeed at exercising. The increased awareness and the ability to find solutions led several participants to be more determined in following through with their plans. Some said they could more easily reschedule their activities when unexpected events occurred. Based on the observations of the different values that participants obtained from using the reflection tool, we recommend looking at the short-term and long-term impact of data-driven IIMC within the individual and collaborative context. It is also worth examining how this technique can influence awareness, determination, and ability to respond to unexpected changes to planned schedule.

4.3 Lessons for Future Research on Data-Driven Implementation Intention with Mental Contrasting

Some of our observations point to areas where future research is needed to further inform the design of data-driven IIMC.

4.3.1 Study Micro and Macro Reflection on Data for IIMC. We observed 'micro-reflection' in the form of paying attention to one's behaviors in the very recent past and within a short window of time at the time of logging. We also observed 'macro-reflection' in the form of examining patterns of behavior over an extended period of time from one to three weeks. Both seemed to be important in more effectively applying IIMC. Micro-reflection seemed to help people better notice divergence from desired behaviors as well as the obstacles. Several participants described how they took mental notes on whether they followed their priorities and reasons for deviating from their priorities while recording their activities. Most wanted to be reminded once a day to look back and reflect. Macro-reflection was described as more helpful in identifying opportunities to address the obstacles. For example, one person noticed patterns on days she was more physically active after work: she had completed more afternoon exercise on days with fewer meetings. Seeing that her meetings were all clustered on certain days, she decided to further spread the meetings to be able to more successfully follow her exercise plans.

Much of the past HCI research on implementation intentions has focused on the automatic detection of situations that should trigger action. However, our study highlights the potential for micro-reflections through low-cost and simple logging as a new perspective to supporting detection of situations for IIMC with technology. If micro-reflection is shown to be helpful, we have a way of helping people get better at identifying the relevant situations (i.e., the obstacles that form the if part of if-then plans). Macro-reflections, on the other hand, seem to support the other element of IIMC which were rarely considered in past work: deciding the specifics of actions to take (i.e., the material for the then part of if-then plans). Therefore, future research should examine more closely the value different types of reflections on data bring to the application of IIMC.

4.3.2 *Study Ways to Scaffold the Exploratory Process.*

The inquiry process, the process of generating, testing, and revising hypotheses, is a key aspect of drawing insights through reflection over data [1]. We observed three breaking points in this process. First, some participants needed additional guidance to form a hypothesis. That is, they faced the so-called *'cold-start' problem* where they could not form inquiries around their work-nonwork balance goal. We provided some guidance to help the inquiry process by prompting participants to express the most important obstacle to their desired work-nonwork balance state and identify how the obstacle plays out in their data. However, that was not enough as some participants were still unsure about what they should look for in the data.

The second breaking point of the inquiry process happened for participants who were able to form questions but could not decompose and map their questions to data. For example, one participant was interested in using her data to identify meetings she could cut from her schedule. She was initially unable to do so with her data. But as she explained her objective, she realized she would like to know if she is engaging in other activities during a meeting, as multi-tasking during a meeting is a sign that the meeting is not the best use of her time. The next challenge for her was *operationalizing* multi-tasking within her data. She did not first realize that she should look for time slots with one or more activities besides meetings.

We observed that participants who effectively explored their data were able to navigate up and down a hierarchy of questions. A common exploratory flow started with questions such as "how am I spending my time?", then moved on to "how consistent is the way I spend my time with the way I want to spend my time?" and later to "what are better ways of spending my time?" The third breaking point happened when participants stopped prematurely in the exploration flow.

Further investigation into ways to scaffold around these breaking points can significantly improve data-driven reflection and behavior planning. For example, it would be useful to know whether providing a list of 'seed' sample questions for people to appropriate and personalize may be helpful. Similarly, techniques to enable decomposing and operationalizing hypotheses are important to study, as are those to support individuals to move up levels of reflection.

4.3.3 *Study the Social Aspects of Planning for Improving Work-Nonwork Balance.*

We noted above that participants wanted to take insights from data to have conversations with their managers and teammates as a way of managing externally influenced obstacles. A few participants in management roles additionally commented on the opportunities for improving employee workload and satisfaction if their direct reports shared similar information with them. For example, a senior program manager overseeing the work of multiple program managers described the potential use of activity data to shed light on the less defined work that program managers are doing. While acknowledging concerns around privacy and power dynamics, he added how such information would be helpful in ensuring proper expectations are set and that program managers are not overworked. The social aspects of using data to identify obstacles and working through them for improving work-nonwork balance within IIMC and more broadly in the context of well-being at work, are an important area for further research. It is important to understand and support collaborative aspects of integrating data into goal setting (e.g., employee vs. business orientation in goals), preparation (e.g., what data is useful to record), sense-making (e.g., reflections to identify obstacles), and action (e.g., what situations need to change) in the workplace context. While doing so, we should also be mindful of nuances around employee trust and power dynamics within an organization and mitigate unintended harms.

4.3.4 *Study Techniques and Frameworks for Personalized Data Collection.*

We observed high variability in data that participants found relevant to addressing reflective questions even though they had very similar questions. For example, some people only cared about the distinction between work vs. nonwork while others wanted to differentiate activities at the project level (e.g., meetings for a specific project). Or, some people wanted to record their stress levels, while some others cared more about energy levels. These observations point to the importance of personalized data collection for behavior planning. Therefore, it is important to further study techniques that enable the expression of arbitrary but relevant data.

5 LIMITATIONS

While our work demonstrates that reflection on personal data can support the application of implementation intention and mental contrasting (IIMC), further examination is needed to establish the added value of data-driven IIMC. Specifically, we should compare if data-driven IIMC outperforms standard IIMC in helping individuals realize their goals. Moreover, considering the small sample size of our study we were unable to explore the use of data-driven IIMC across user groups based on age, gender, work and family roles, or other characteristics. A larger more diverse sample can bring to light additional requirements and opportunities.

6 CONCLUSION

We explored whether and how data can support goal setting and realization through implementation intention and mental contrasting (IIMC). In doing so, we built data collection and reflection tools and used them in a probing study. Through this exercise, we gained knowledge about the design requirements and opportunities for tools that bring data to IIMC, considerations for formally studying data-driven IIMC, and areas for additional research in this space. Our case study was focused on applying data-driven IIMC for improving work-nonwork balance in the workplace context. However, the lessons can be useful more broadly for self-reflection and personal informatics research. While additional contextualization in other domains is necessary, designers and practitioners can use these lessons as starting points in approaching their respective challenges.

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