Peerspective: A Study on Reciprocal Tracking for Self-awareness and Relational Insight

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Abstract

Personal informatics helps individuals understand themselves, but it often struggles to capture non-conscious behaviors such as stress responses, habitual actions, and communication styles. Incorporating social aspects into PI systems offers new perspectives on self-understanding, yet prior research has largely focused on unidirectional approaches that center benefits on the primary tracker. To address this gap, we introduce the Peerspective study, which explores reciprocal tracking—a bidirectional practice where two participants observe and provide feedback to each other, fostering mutual self-understanding and collaboration. In a week-long study with eight peer dyads, we explored how reciprocal observation and feedback influence self-awareness and interpersonal relationships. Our findings reveal that reciprocal tracking not only helps participants uncover blind spots and expand their self-concepts but also enhances empathy, deepens communication, and promotes sustained engagement. We discuss key facilitators and challenges of integrating reciprocity into personal informatics systems and offer design considerations for supporting collaborative tracking in everyday contexts.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**.

Keywords

Personal Informatics, Blind Spots, Reciprocal Tracking, Peerspective, Self-Understanding, Social Features in Tracking

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1 Introduction

People engage in the practices of Personal Informatics (PI)—the collection of and reflection on personal data—for purposes such as improving oneself, exploring one's interests, keeping records, and appreciating numerical patterns, ultimately seeking deeper self-understanding [22, 44, 49]. A significant stream of research in PI has focused on solitary practices [22]. However, incorporating social dimensions can significantly enhance its impacts [64, 82]. For example, sharing data with peers or support networks—including friends, family, and online communities—allows individuals to view their behaviors through new lenses [8, 66, 71], receive emotional support [33, 68, 73, 81], and obtain practical advice [61, 68, 96]. These interactions foster deeper reflection and make the PI process more dynamic and engaging.

Building on the benefits of social engagement in personal informatics, the field is evolving from traditional models where others passively receive shared data to more active and integrated forms of collaboration, often referred to as collaborative tracking [25, 59, 69, 78, 79, 95]. In clinical and family settings, delegated trackers, including clinicians and parents, actively assist in tracking by collecting data on behalf of individuals—such as patients or children—who may struggle with self-monitoring [29, 39, 109]. This collaborative approach enables effective condition monitoring while fostering a supportive environment. For example, Hoefer et al. introduced a co-tracking system for patients managing bipolar disorder and their caregivers, where both parties observed, recorded, and shared data about each other [34]. Through this mutual interaction, patients gained new insights from their caregivers, deepening their self-understanding while caregivers improved their empathic accuracy, allowing them to provide more effective support.

However, prior research has largely focused on *unidirectional* involvement, centering on the benefits for the primary tracker, such as gaining diverse perspectives and achieving deeper self-understanding. While the contributions of those providing data—like caregivers or peers—are acknowledged, the focus often remains on how their input supports the primary tracker, with little attention paid to the benefits they might gain for themselves. *Bidirectional* co-tracking, where both parties actively observe and learn from each other, presents an opportunity to address this gap. Social psychological theories suggest such mutual observation not only helps uncover blind spots [58, 103]—subtle personal traits or non-conscious behaviors such as stress responses, habitual actions, and communication styles—but also fosters observational learning [5], encouraging both parties to reflect on their own behaviors through comparison. These processes create a deeper level of self-awareness and can enhance empathy and mutual understanding [39, 65, 94, 109], ultimately offering reciprocal benefits to all participants. These insights lay the foundation for the concept of **reciprocal tracking**, where participants engage in a bidirectional exchange by not only sharing data but also actively observing and learning from one another. Reciprocal tracking builds on existing collaborative tracking approaches by fostering mutual observation and creating shared benefits that enhance both self-understanding and relationship dynamics.

To further investigate the potential of reciprocal tracking, we propose the *Peerspective Study*, a structured exploration of how reciprocal tracking practices between peers can foster deeper self-awareness and improved interpersonal relationships. In this study, pairs of peers engage in daily activities that include observing each other's behaviors, providing constructive feedback, and reflecting on their shared experiences. The term Peerspective—a blend of 'peer' and 'perspective'—emphasizes the unique value of peers in fostering open communication and meaningful feedback within shared contexts. Building on this concept, our study addresses the following research questions:

- RQ 1. How does participation in the Peerspective Study, involving mutual observation and data-sharing, impact each individual's self-understanding?
- RQ 2. How do the mutual understanding and empathy developed through the Peerspective Study influence participants' interpersonal relationships?
- RQ 3. What are the facilitators and challenges that emerge during the implementation of the Peerspective Study?

To investigate these questions, we conducted a week-long diary study with eight peer dyads, including roommates, friends, coworkers, and romantic partners. We selected pairs with close physical and psychological proximity to facilitate smoother and more meaningful feedback exchanges [31, 54, 63]. Our findings revealed that reciprocal tracking makes participants enhance their self-understanding and gain motivation to explore themselves further, even without directly self-tracking their behaviors, by reflecting on their partners' observations and feedback. Through repeated observation, participants refined their mental models of their peers, allowing them to infer not only explicit behaviors but also implicit aspects. This process supported their partners' self-understanding through context-aware feedback. Furthermore, the mutual data-sharing process fostered shared activities and deeper conversations, enhancing interaction and communication. Building on these findings, we discuss how reciprocity can be integrated into PI systems, how reciprocal tracking can be facilitated in everyday contexts, and how privacy concerns, data relevance, and emotional burden can be addressed to ensure actionable integration.

The contributions of this work are:

(1) We propose a reciprocal tracking approach, demonstrating how mutual observation and feedback can potentially enhance self-understanding for participants;

(2) Through the Peerspective study with eight peer dyads, we empirically examine participants' experiences with reciprocal tracking, shedding light on its potential to enrich personal informatics by fostering collaboration and social engagement among peers;

(3) We identify key facilitators and challenges of reciprocal tracking, providing practical insights for integrating social features into personal informatics and addressing obstacles to designing effective reciprocal tracking tools.

2 Related Work

2.1 Self-Understanding with Personal Informatics

Personal informatics is a field that explores methods to enhance self-understanding by collecting and analyzing personal data [44, 49]. Self-tracking serves as a key tool for self-understanding, allowing individuals to monitor their health, manage chronic conditions, or change habits [1, 14, 22, 72]. While self-tracking data often relates to health, wellness, and fitness [18, 99], it can also cover aspects of daily life such as financial status, locations visited, and food consumed [26]. Advances in digital technology have made self-tracking much more convenient and efficient. Simple self-reporting interfaces allow users to quickly and easily log data such as mood, sleep quality, and water intake [12, 101, 110]. Additionally, smartphone apps and wearable devices automatically collect a wide range of biometric data, including physical activity [19], sleep patterns [12, 43], and heart rate [15], enabling data to be captured continuously without the user's awareness. By automating data collection, this technology reduces user burden and supports the potential for long-term self-tracking [7, 11]. Furthermore, advances in machine learning and artificial intelligence help to reduce the cognitive burden of analyzing collected data, offering personalized support through predictions and recommendations, fostering deeper self-understanding [20, 36, 48]. Consequently, digital technology enables self-trackers to derive meaningful insights with less effort, enhancing their self-understanding.

However, self-tracking alone still has limitations in achieving complete self-understanding. Despite the introduction of automated tracking methods, technical challenges can impede seamless data collection [11], and not all types of data can be automatically captured [1]. Automated systems, while being effective in detecting trends and correlations, often fall short in capturing subjective, context-sensitive elements, or identifying causal factors, such as the triggers of stress or emotions [41, 42]. Moreover, automatically collected data may decrease user engagement and awareness, potentially leading to a weakened understanding and interpretation of the data [11, 50]. Similarly, manual self-reporting methods face comparable issues. Users may generate unreliable data due to recall bias, delayed recording, or inaccurate entries during the data input process [6, 11, 62, 98]. Such inaccurate data makes it challenging to extract meaningful insights [14, 49], and users may interpret the data with a biased perspective [27, 67, 85], especially when faced with negative outcomes, leading to selective or distorted interpretations [28]. These limitations highlight a gap in capturing the contextual and temporal dimensions of users' lives, which are crucial for meaningful self-reflection [83, 84]. By integrating data that reflects users' broader life contexts, personal informatics systems could better connect actions to their underlying meanings, fostering more comprehensive self-understanding.

2.2 Enhancing Awareness Through External Feedback

Johari's Window model provides a valuable perspective on self-awareness, particularly in recognizing both conscious and unconscious biases [58]. The model divides self-perception into four areas: the 'Open Area' (known to self and others), 'Blind Area' (known to others but hidden from self), 'Hidden Area' (known to self but hidden from others), and 'Unknown Area' (unknown to both self and others). Of particular relevance is the 'Blind Area,' which includes non-conscious behaviors such as habitual actions, stress responses, and social interactions—areas that self-tracking alone may struggle to capture. Feedback from others plays a crucial role in uncovering these blind spots, making it essential to incorporate social features to deepen self-understanding.

Although personal informatics has traditionally focused on individual tracking [22], its potential can be significantly enhanced by incorporating external perspectives [64, 82]. Research in Human-Computer Interaction (HCI) shows that social features, such as sharing data with others and engaging in collaborative tracking [25, 59, 69, 78, 79, 95], provide new insights [8, 66, 71], emotional support [33, 68, 73, 81], and practical advice [61, 68, 96]. For example, individuals often share their tracking experiences and tracked data online to communities of self-trackers offer fresh viewpoints and hold each other accountable [16, 24, 70, 73, 100]. In cases where tracking is difficult—such as for individuals with chronic conditions—caregivers, clinicians, or family members can step in to track data on their behalf, offering detailed and comprehensive information for better patient care and management. This process can also enhance caregivers' understanding of the patient's health conditions, allowing them to offer more informed support [39, 65, 94, 109]. This kind of social support has been shown to improve health outcomes, including physical fitness, mental health, and healthy eating [32, 77, 92, 105]. Research highlights that interactions with others bring added value to the self-tracking experience, suggesting the need to further explore how social factors influence personal informatics [91]. Our research expands on these insights by exploring how external feedback helps users identify blind spots and uncover areas they may not recognize, offering new possibilities for gaining richer and more personally meaningful insights.

2.3 Mutual Engagement and Shared Benefits through Reciprocal Tracking

Engaging people in personal informatics not only enriches their data but also fosters greater involvement in tracking, laying the groundwork for long-term use [51, 76, 86]. For instance, integrating gamified elements such as virtual rewards, leaderboards, and rankings can increase engagement by encouraging competition or collaboration [31, 87]. However, excessive competition may lead to discomfort [60, 107], causing users to avoid competitors or withhold data [60, 108]. While social features have been developed to sustain engagement, participation often declines once the novelty wears off, highlighting the persistent challenge of maintaining long-term interest in personal informatics [16, 23, 53, 60, 107]. Previous research indicates that social connectedness fosters sustained self-regulation and adherence to health activities, as individuals are more likely to maintain habits and achieve goals when supported by others [89]. Engaging peers, caregivers, or family members strengthens accountability and emotional support while empowering supporters to take a more active role [37]. For collaborative tracking to be effective, those providing support should not be confined to a passive role of mere data collectors [8, 29]. Instead, active involvement in both data collection and interpretation fosters a deeper connection and enables supporters to provide more meaningful contributions [57, 66, 79, 94].

While prior research highlights the value of involving supporters, current studies focus on primary trackers, often neglecting potential benefits for those assisting in tracking. Recent co-tracking research highlights how collaborative approaches, such as mutual observation and data-sharing, can lead to shared benefits. For instance, Hoefer et al. demonstrated that co-tracking between caregivers and patients managing bipolar disorder deepened patients' self-understanding while fostering caregivers' empathy [34]. However, these studies primarily focus on structured settings like clinical environments, where feedback tends to be unidirectional. In contrast, our work explores how reciprocity—a social norm that encourages mutual effort [30, 97, 104]—can address this gap. By fostering balanced, bidirectional exchanges, reciprocal tracking not only creates shared benefits for all participants but also sustains their motivation and engagement in everyday contexts. This approach provides a new framework for integrating social dynamics into personal informatics, complementing and extending traditional collaborative tracking practices.

3 Method

This study aims to explore how peer perspectives can be leveraged to foster self-reflection and expand self-awareness, focusing on how participants engage with reciprocal tracking in real-world settings. We designed an experiment involving pairs of close acquaintances to investigate how this method could help participants uncover blind spots in their behavior, providing new perspectives that facilitate deeper self-understanding. In this section, we describe the processes involved in the Peerspective study, including how participants were recruited, how materials and procedures were designed to facilitate reciprocal tracking, and how the data generated by participants were analyzed. The study was conducted following the approval of the Institutional Review Board (IRB).

3.1 Recruitment

We recruited participants by publicizing the experiment as an opportunity for individuals interested in enhancing self-awareness through peer perspectives, emphasizing its focus on uncovering behavioral blind spots by observing and exchanging feedback with a partner. Recruitment notices were posted on bulletin boards at two universities and disseminated through word of mouth, encouraging individuals to apply in pairs by completing a survey form. The survey collected information about participants' relationship type (e.g., friends, coworkers, romantic partners), how long they had known each other, the frequency of their meetings, and the amount of time they typically spent together. These details were crucial for assessing the suitability of pairs, as the nature of reciprocal tracking requires close observation and meaningful feedback. Previous studies suggest that familiarity fosters authentic interactions, smoother exchanges, and reduced concerns around privacy and data relevance [31, 40, 54, 63, 102]. By prioritizing pairs with established relationships, we aimed to ensure the quality of feedback and support meaningful engagement throughout the study.

From the initial pool of 33 interested pairs, we prioritized participants based on three key criteria. First, we selected pairs who had known each other for over two years, as this duration was considered sufficient to establish familiarity and understanding. Second, we emphasized frequent interaction, defined as meeting at least four days per week and spending more than five hours together per day. Lastly, relationship dynamics and gender balance were also considered to ensure diverse perspectives within the sample. Based on these criteria, we selected nine pairs, consisting of four pairs of friends, three pairs of coworkers, and two pairs of romantic partners. However, one pair of friends (P5, P6) withdrew from the study due to conflicts during the feedback exchange, leaving eight pairs (16 participants: 9 female; mean age = 24.3 years, SD = 2.8) who completed the experiment (See Table 1). All participants provided informed consent before the study began. Participants who completed both the workshop and the interview received a compensation of 70,000 KRW (approximately 52 USD). To better understand the dropout case, we conducted separate follow-up interviews with each participant to gain insights into the challenges of reciprocal tracking. These participants were compensated with 20,000 KRW (approximately 15 USD) for their time.

3.2 Peerspective Study Design

3.2.1 Introductory Workshop. An introductory workshop was held with both participants to introduce the concept of reciprocal tracking, clarify its objectives, and provide a structured framework for initiating the study (See Figure 1 A). To help participants gradually familiarize themselves with each other before engaging in more personal reflections, we designed a worksheet that guided them to first explore shared contexts before moving on to identifying potential blind spots (See Figure 2 A). The workshop lasted approximately one hour. One of the key purposes of the workshop was to address privacy concerns, a common issue when applying social features to personal informatics [21, 71, 78]. Observing another person inherently raises ethical questions about boundaries and the potential invasion of privacy. Drawing on insights from prior studies, the session encouraged participants to openly discuss these challenges and negotiate boundaries for data collection and feedback exchange. This included defining how to handle sensitive information and establishing guidelines for respectful interaction. By fostering mutual understanding, setting clear expectations, and aligning the tracking activities with both participants' comfort levels, the workshop aimed to minimize potential conflicts, build trust, and ensure that the reciprocal tracking process remained both meaningful and comfortable [47]. The workshop involved several key activities:

Defining Relationship and Environment (See Figure 2 A-1): Participants described their relationship and categorized environmental factors using keywords. One circle represented their own environment (e.g., interests, hobbies, routines), and the other captured their partner's environment. Outside the circles, they noted commonalities such as shared spaces, activities, or acquaintances. By recognizing shared contexts, participants could establish a sense of connection and comfort, which facilitated smoother transitions into the later stages of identifying blind spots.

Identifying Blind Areas (See Figure 2 A-2): Using their background knowledge of each other, participants explored six common blind areas—habits, personality traits, communication style, emotional triggers, stress responses, and hidden strengths or weaknesses—specifically focusing on aspects their partner might not be aware of. They then exchanged worksheets to share, discuss, and refine their observations. Insights gained from these discussions were then recorded in the third section of the worksheet (See Figure 2 A-3).

Setting Exploration Goals (See Figure 2 A-4): After introducing the concept of reciprocal tracking, participants identified specific blind areas they wanted their partner to observe over the week (See Table 1). This activity was designed not to limit the scope of observation but to provide a structured starting point, especially for participants who might otherwise feel uncertain about what to observe. Defining these areas allowed participants to concentrate on their initial observations while remaining free to explore additional behaviors or patterns beyond the predefined domains.

3.2.2 Reciprocal Tracking. Participants then engaged in a week-long reciprocal tracking exercise using a kit with three types of cards (See Figure 1 B): (1) Observation Log Card 🔎, (2) Analysis Card 📊, and (3) Reflection Card 🤔 (See Figure 2 B,C,D). This process was designed to ensure systematic observation, analysis, and reflection, with each step building upon the previous one. We used written forms grounded in research suggesting that writing out one's thoughts can significantly enhance self-awareness [38].

Each day, participants observed their partner and documented their findings on an observation log card (See Figure 1 B-1), designed to capture both objective details and subjective impressions. The card consisted of two parts. The first part focused on describing the observed behavior, including details such as time, location, and context. Participants could use text or drawings to document these observations comprehensively. The second part was an optional free note section, where participants could record their initial impressions or thoughts about the observed behavior. This allowed participants to freely express their interpretations or hypotheses, offering a space for more subjective and reflective input. Participants were required to complete at least one log per day but were not limited in the number of entries. To accommodate varying levels of engagement, 30 log cards were provided for the week, ensuring ample space for documentation.

Based on their observation logs, participants filled out an analysis card designed to synthesize their findings and provide meaningful feedback to their partners (See Figure 1 B-2). The analysis

Table 1: Demographics of Peerspective Study participants, context of the dyad of peers (relationship, how long they have known each other, how many days per week they meet on average, and how many hours they spend together on average when they meet), and the list of blind spots participants defined as those they wanted to discover through their partner during the introductory workshop. D3, marked with *, withdrew on the third day of the experiment.

Alias	Participants	Gender	Age	Occupation	Context	Blind spots participants seek to explore
D1	P1	F	22	Graduate Student	• Colleague (in the same lab) • Known for 6 months • Meet 3-5 days a week • Spend over 5 hours together per day	• Unhealthy habits in daily routines • Work patterns (Is my focus too short? Am I too distracted?) • Conversational habits (Am I too emotional or too playful?)
	P2	F	23	Graduate Student		• Moments of anger and perceived success • Moments when strengths and weaknesses become apparent
D2	P3	F	24	Internship in a company	• Colleague (in the same office) • Known for 5 years • Meet almost every day • Spend 3-5 hours together per day	• When perfectionist tendencies show up • My usual mindset
	P4	F	23	Office worker		• What I feel most anxious about • What seems important to me • My selfish tendencies
D3*	P5	F	29	Job Seeker	• Friend • Known for 3 years • Meet almost every day • Spend 1-3 hours together per day • Working at the same part-time job	• Emotional triggers as seen by others (because I can't express them well myself)
	P6	F	26	Job Seeker		• How I appear and feel when walking down the street or when others meet me • When I appear mature
D4	P7	M	26	Undergraduate Student	• Friend (in the same university) • Known for 3 years • Meet almost every day • Spend 5 hours together per day	• How I appear to others, including my personality
	P8	M	23	Undergraduate Student		• Habits or mannerisms
D5	P9	M	26	Graduate Student	• Colleague (in the same lab) • Known for 2 years • Meet 3-5 days a week • Spend over 5 hours together per day	• What triggers my emotional ups and downs
	P10	M	31	Graduate Student		• Strengths and weaknesses I'm unaware of • Habits that would be good to change
D6	P11	F	28	Office worker	• Fiancé (getting married next year) • Known for 5 years • Meet almost every day • Spend over 5 hours together per day • Living together since a week before the study	• Bad habits I'm unaware of • Things you wish I would change
	P12	M	27	Office worker		• Habits or behaviors I should fix • Weaknesses
D7	P13	F	23	Undergraduate Student	• Friend • Known for 5 years • Meet almost every day • Spend 1-3 hours together per day	• Emotional changes or unnoticed behaviors I'm unaware of
	P14	M	22	Undergraduate Student		• My emotional self • What I like, what I dislike, and what makes me happy
D8	P15	F	22	Undergraduate Student	• Romantic partner • Known for 3 years • Meet almost every day • Spend over 5 hours together per day	• Small daily habits
	P16	M	25	Graduate Student		• Want to know all my weaknesses in detail
D9	P17	F	26	Undergraduate Student	• Friend (roommate) • Known for 4 years • Meet almost every day • Spend over 5 hours together per day	• What triggers my emotional ups and downs
	P18	F	22	Undergraduate Student		• Patterns in my speech or behavior • Am I someone who easily shows negative emotions? • Habits I don't realize I have

card consisted of three parts. The first part required participants to summarize their observations. While they were not expected to include every detail from their logs, participants were encouraged to present their summaries in a clear and concise manner to ensure their partner could easily understand the context and key points. In the second part, participants identified potential blind spots—behaviors or patterns their partner might not be fully aware of. This section aimed to highlight insights that could prompt deeper reflection. Finally, the third part focused on providing actionable recommendations related to the identified blind spots. Participants suggested behaviors or strategies they believed could support their partner's growth or self-awareness. These analysis cards were exchanged at predetermined times agreed upon during the workshop, ensuring a consistent and structured process for sharing and receiving feedback.

Upon receiving their partner's analysis card, participants used the reflection card to reflect on the feedback and insights gained (See Figure 1 B-3). The reflection card consisted of three parts. The first part invited participants to document their thoughts as observers, focusing on what they learned about themselves while observing their partner. Drawing on Albert Bandura's Social Cognitive Theory [5], we emphasized that the act of observation itself can

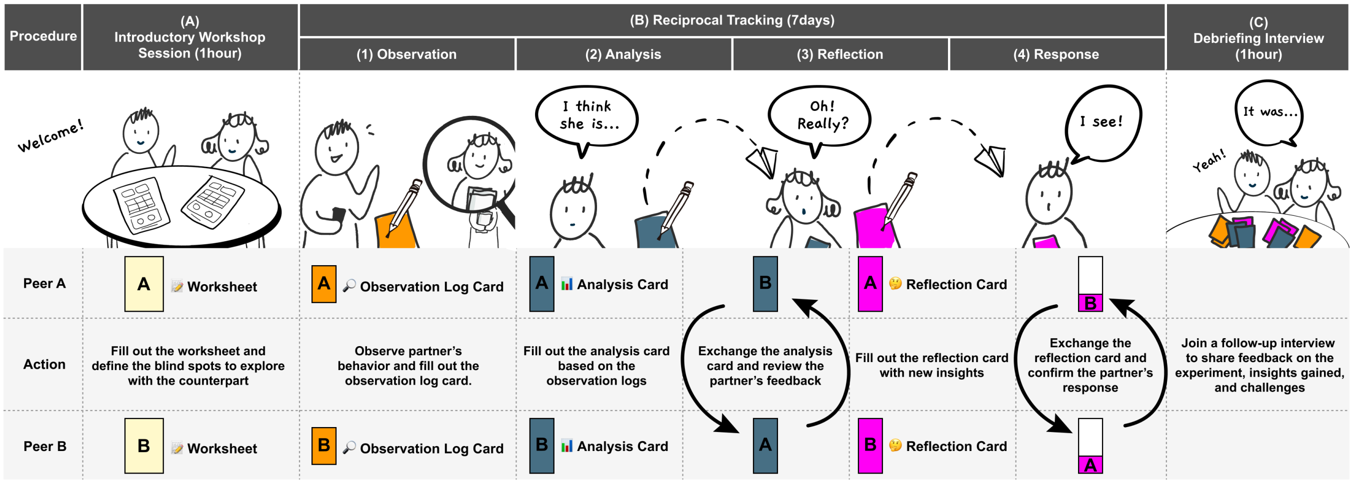

Figure 1: Peerspective Study Procedure: (A) Dyad of peers attend an introductory workshop and fill out worksheets to define the blind spots they want to explore through their partner's observations. (B) The two participants engage in Reciprocal Tracking for one week. Each day, participants: (1) Observe their partner and fill out an observation log card, (2) Fill out an analysis card based on their observations and exchange cards, (3) Fill out a reflection card with the data received from their partner and exchange cards, (4) Review their partner's response to the data they provided through a response note. (C) After the one-week reciprocal tracking, participants take part in a debriefing interview about the study.

lead to observational learning, enabling participants to compare observed behaviors to their own, internalize insights, and adjust their actions accordingly. In the second part, participants reflected on the insights gained from their partner's analysis card. This section encouraged them to compare the feedback they received with their own experiences and daily behaviors, identifying areas of alignment or discrepancy to uncover new perspectives. Finally, the third part provided space for participants to respond to the feedback and actionable recommendations shared by their partner. This section allowed participants to offer their reactions, clarify misunderstandings, or express gratitude for the insights provided. To respect participants' privacy, only the response section from the reflection card was exchanged with their partner at the agreed-upon time, while the other sections remained private for personal use (See Figure 1 B-4).

Each pair decided on the timing for exchanging cards during the workshop. Most participants chose to exchange the analysis cards in the evening, followed by the reflection cards about an hour later. To ensure the process was reciprocal, unbiased, and privacy-conscious, researchers facilitated the exchange as intermediaries. Participants submitted photos of their completed cards to the researchers, who only exchanged the cards after both participants had submitted their entries. This prevented one participant's data from influencing the other's responses, preserving the authenticity of individual observations. Additionally, researchers ensured that only the designated sections of the cards were shared. For example, in the reflection card, only the response section was sent to the partner, while the remaining sections, which contained personal reflections, were kept private. This safeguarded participants' privacy and minimized the risk of accidental disclosure. In cases where one participant had not submitted their card by the agreed-upon time, researchers contacted them to ensure timely completion, maintaining the reciprocal nature of the exchange. The role of the researchers was strictly limited to logistical facilitation. We acted as a neutral channel for data transfer, ensuring smooth communication while avoiding any involvement in the content of the cards. This approach allowed participants to engage in meaningful, self-directed exchanges while addressing practical challenges, such as privacy protection and adherence to the agreed schedule.

3.2.3 Debriefing Interview. At the end of the reciprocal tracking period, participants took part in a follow-up interview together (See Figure 1 C). The interview aimed to gather feedback on the overall experiment, including their thoughts on the process, the materials used, and any new insights gained about themselves or their partner. We also inquired about any challenges they faced in collecting and sharing data, especially when dealing with their partner's information, as well as the benefits and difficulties of working with a partner. Additionally, we conducted separate interviews with participants who had dropped out of the study to understand why they decided to leave, what issues arose between them, and what challenges they encountered during the process.

3.3 Data Analysis

We analyzed data obtained from the introductory workshop, reciprocal tracking phase, and debriefing interviews. All sessions were audio-recorded and transcribed for in-depth analysis. For the data generated during the introductory workshop and reciprocal tracking phases, we focused on the 16 participants who completed the reciprocal tracking, excluding the dropout case. However, for the debriefing interviews, we reviewed data from all 18 participants, including the dropout case. Participants generated a total of 211 observation logs during the reciprocal tracking phase (Mean: 13.2

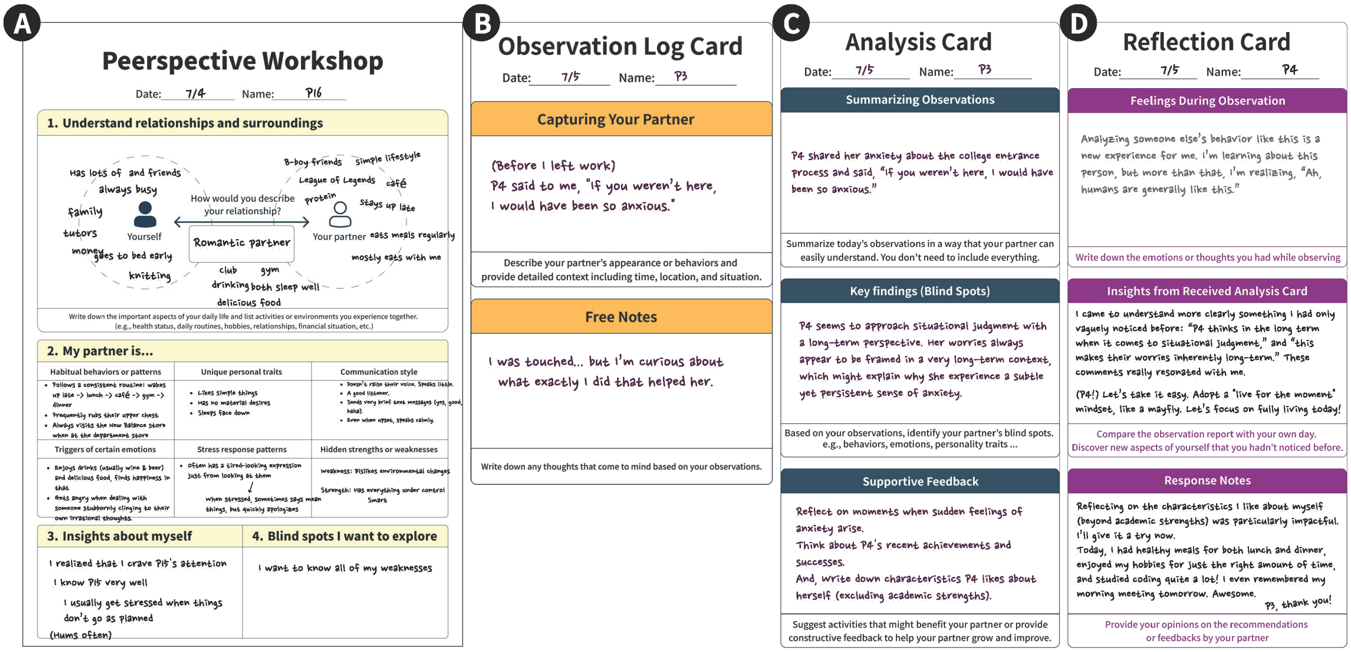

Figure 2: Examples of Workshop and Reciprocal Tracking Data (The content was translated into English from what participants actually wrote, and participant names were coded to ensure anonymity): (A) Worksheet written by P16 during the introductory workshop, (B) An observation log card written by P3 after observing P4, (C) An analysis card created by P3 based on the observation log card, (D) A reflection card written by P4 after receiving P3's analysis card (Note: The 'feeling during observation' section at the top reflects P4's feelings while observing P3 and is unrelated to the data provided by P3; thus, its transparency has been adjusted)

logs, SD: 3.67, approximately 1.9 logs per day). All participants also completed analysis cards and reflection cards as required.

Our main objective was to investigate the behaviors participants observed, the feedback they exchanged, and the impact of their partner's perception on their self-understanding. To ensure participant anonymity and data privacy, we coded all identifiable information before performing a qualitative analysis. We conducted a thematic analysis [17] to examine the data. Two lead authors familiarized themselves with the data by reading through the field notes and interview transcripts multiple times. We then conducted an iterative process for inductive coding aligned with the objectives of our research, identifying initial codes from the data. Based on these initial codes, we developed six preliminary themes: (1) Observation and its Adaptation, which captured participants' overall experiences of observing counterparts and the shifts in their focus over time; (2) Self-Awareness, which focused on the development of self-concept through observation and the application of feedback; (3) Social Dynamics, which addressed the influence of reciprocal tracking on social interactions and relationship building; (4) Characteristics of Delivered Feedback, which highlighted the types and styles of feedback provided; (5) Reception to Feedback, which explored participants' emotional and behavioral reactions to the feedback they received; (6) Benefits and Challenges of Reciprocal Tracking, which identified the strengths and difficulties encountered during the process. These themes served as an initial structure for further analysis. The two lead authors then continued inductive coding on the remaining data, identifying additional patterns and refining the themes iteratively. We discussed and resolved discrepancies, revising the themes as needed. Through this iterative process, four key themes were finalized: the evolution of participants' observation experiences, the expansion of self-concept through reciprocal tracking, the role of feedback in fostering mutual engagement, and the relational effects of reciprocal tracking.

4 Findings

Our participants reported that the experience of observing each other and exchanging feedback was highly engaging, noting that it significantly contributed to their understanding of themselves. In this section, we describe how participants observed each other, the types of data exchanged, the impact of data on self-perception and mutual relationships, and the challenges encountered during the process.

4.1 Overall Observation Experience

Through the data generated by participants and interviews, we explored participants' overall experiences with reciprocal tracking. Participants described their experiences as extending beyond simple observation, emphasizing curiosity and a deeper effort to understand the *'why'* behind behaviors. As P4 reflected, *"This process wasn't just about observation; it was about developing curiosity toward the person I was observing. When I noticed certain behaviors, I couldn't help but wonder, 'Why did she act in that way?' I*

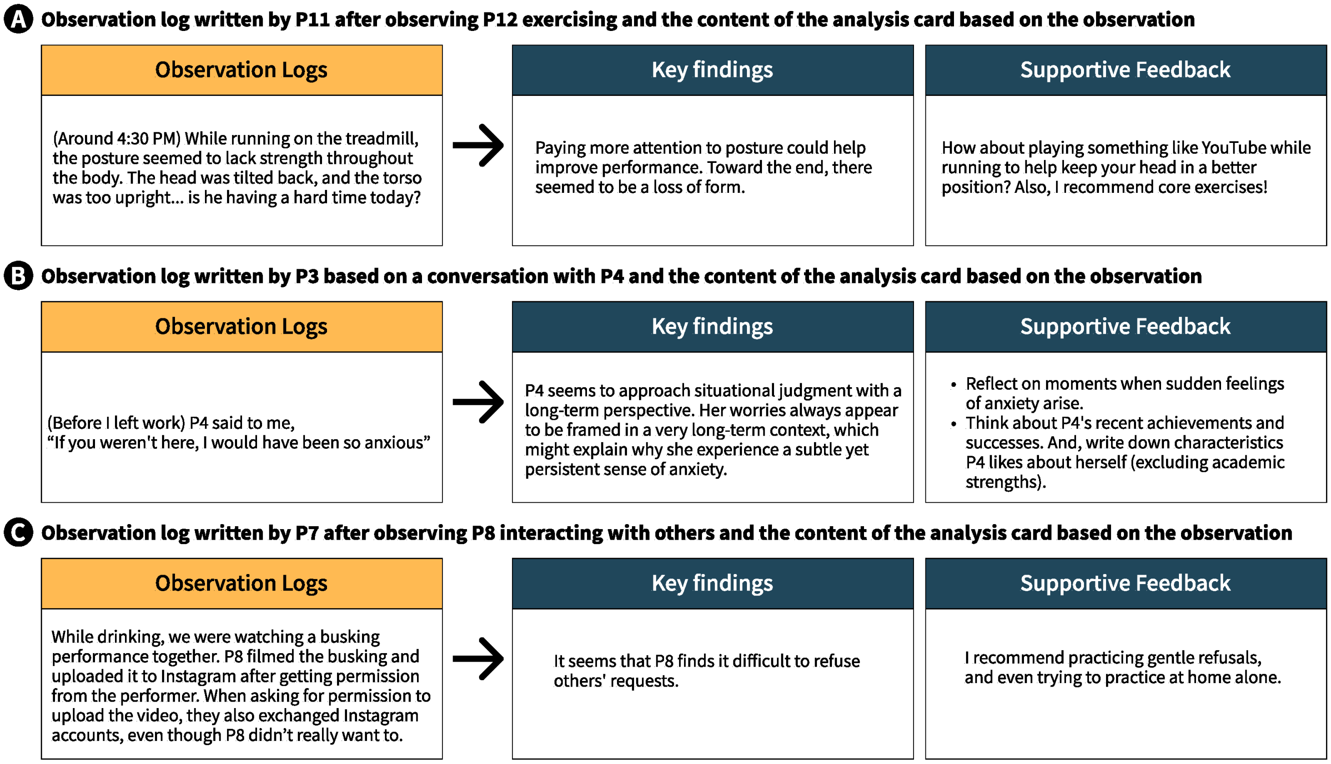

Figure 3: Examples of Observation Cards and Analysis Cards Written by Participants (The content was translated into English from what participants actually wrote, and participant names were coded to ensure anonymity): (A) P11's observation log of P12 exercising and the corresponding analysis card, (B) P3's observation log of a conversation with P4 and the corresponding analysis card, (C) P7's observation log of P8 interacting with others and the corresponding analysis card.

began to consider her mood or the values that might be influencing her actions. For this reason, I believe 'curiosity' is a more accurate term than 'observation.'" However, participants also encountered challenges during the observation process and expressed concerns about recording and sharing sensitive details in their logs.

4.1.1 From Surface-Level Observations to Contextualized Insights. Participants initially focused on visible behaviors or appearances in their feedback. For example, P11 noted that P12's posture while running on the treadmill was incorrect and offered suggestions for improvement (See Figure 3 A). P14, aware that P13 had been working to lose weight for some time, observed dimples forming on her face and commented that it was a clear sign of weight loss. In addition to these examples, participants shared insights based on directly observable behaviors such as facial expressions, tone of voice, reactions in specific situations, and text message patterns.

Over time, however, their observations evolved to include more nuanced patterns and interpretations. They began to notice unconscious habits, body language, and consistent behavioral tendencies, leveraging their background knowledge to infer motivations and emotions behind these actions. For instance, P1 noticed her counterpart (P2) eating spicy food and interpreted it as a sign of stress. P3, after observing P4 expressing concerns about the college entrance process, speculated on P4's personality and the reasons behind her worries (See Figure 3 B). In addition to these inferences, participants identified a range of internal dynamics, such as emotional expressions, personal goals and motivations, and the tendency to be aware of others' opinions. While these interpretations were subjective and sometimes speculative, they demonstrated participants' efforts to contextualize their observations and understand their counterparts' internal states, uncovering layers of behavior often overlooked in surface-level interactions.

In addition to observing implicit dynamics, participants paid close attention to how their counterparts interacted and built relationships, offering insights into their social skills and relational attitudes. For instance, P9 gained an understanding of his counterpart's personality and social relationships by noticing how he cared for others and reciprocated favors. Similarly, P7 identified his counterpart's difficulty in saying no during interactions (See Figure 3 C). Other observed behaviors included building relationships through humor, showing respect when interacting with elders, being considerate, and taking responsibility for others' concerns as if they were their own.

4.1.2 Challenges and Adaptations in Observing Counterparts. Participants occasionally faced challenges in observing their counterparts due to not always being in close proximity. For instance, coworkers or lab mates found it difficult to track each other's behavior if they were seated far apart or working on separate projects. Similarly, roommates or friends struggled to observe one another when spending weekends apart. Despite these obstacles, participants made concerted efforts to gather information for their observation logs. They would casually inquire about the other person's day, engage in phone or text conversations to gauge reactions, and review past chat histories or social media posts to gain a better understanding of their counterparts' characteristics.

Beyond logistical difficulties, participants faced both emotional and practical challenges in drawing meaningful insights from their observations. Many participants felt pressure to identify blind spots their counterparts might not usually notice, which led to anxiety about the adequacy of their contributions. P2 explained, *"I wanted to point out things my counterpart might not be aware of and offer constructive suggestions, but it was hard to give advice when I couldn't find anything new."* This pressure was compounded by the repetitive nature of daily observations, which participants found both demanding and burdensome. As P8 shared, *"Trying to avoid repeating observations did help me notice new aspects of my counterpart, but the daily repetition was still quite demanding."* In addition to these challenges, participants also grappled with the awareness of being observed, which temporarily influenced their behavior. P10 remarked, *"I was more cautious and tried to present myself in a better light. If the experiment had lasted longer, I think my behavior would have become more natural, and I would have learned more about myself through my counterpart."*

4.2 Self-Discovery Through Reciprocal Feedback

4.2.1 Reflective Insights From Peer Observations. The analysis card provided by observers offered recipients valuable opportunities for self-reflection. As participants reviewed documented observations of their own behaviors, many described the experience as akin to reading a diary—except from another person's perspective. This external view sparked curiosity and encouraged them to reconsider or analyze the motivations behind their actions. For example, P4 mentioned, *"This experiment made me want to video-record my day like a documentary film. I became curious about what new aspects of myself I might discover, and I was able to clearly identify the reasons behind my actions,"* illustrating how the observations significantly contributed to self-reflection. Even when the observations were not perceived as entirely accurate, they still prompted recipients to reflect on their behaviors and broaden their self-awareness. As P18 noted, *"I couldn't say that what P17 pointed out was 100% correct. However, it made me reflect on my actions, realizing that others might see me in this way."* However, when observations lacked sufficient context or were based on one-off incidents, recipients sometimes found it challenging to accept the feedback and even questioned its validity. For instance, P13 mentioned, *"I usually don't make mistakes, but that day I was tired and probably sent the wrong message. That's why I wrote in the response note that I couldn't agree with P14's feedback."*

Our analysis identified two key factors that enhanced participants' self-reflection. First, the written format of the feedback had a lasting impact, allowing for deeper reflection. As P3 noted, *"In everyday conversations, I have to react quickly, so there's little time to really think about the feedback. Even if it's negative, I would usually just say 'okay' or 'I see' and move on. But with written feedback, I could think it over calmly and really absorb it."* This suggests that the act of reviewing written feedback made it more substantial and meaningful, allowing for a more thoughtful processing of the information. Second, the existing trust played a crucial role in deepening self-reflection. Most felt confident in their understanding of their counterpart's intentions, which allowed them to accept the feedback without conflict or misinterpretation. P14 emphasized, *"The way I accept feedback can depend on who it comes from. With P13, I understand her intentions, but from someone else I didn't know well, it could cause conflict."* This highlights the importance of trust in facilitating open and meaningful exchanges.

4.2.2 Expanding Self-Knowledge Through Feedback. The feedback provided by their counterparts led to meaningful shifts in their self-concept. Our analysis of the personal insights recorded on participants' reflection cards revealed three key areas where their self-knowledge expanded.

Blind spots: Participants uncovered aspects of themselves they were previously unaware of—referred to as 'blind spots' because these ingrained or unconscious behaviors are hard to recognize without external feedback. This feedback brought these hidden behaviors to light, helping participants gain clearer insight into their actions and habits. For instance, P3 realized she often used a defense mechanism after P4 pointed out,*"Why do you keep asking, 'I look really bad today, right?'"*. This made P3 aware of her defensive expressions. Other participants noticed that certain behaviors were more frequent or intense than they had thought. P10 and P18 discovered that their inner emotions were more visible to others through their facial expressions or nonverbal cues, while P15 came to terms with his loss of self-discipline and acknowledged living more recklessly than intended. This feedback played an essential in helping participants identify previously unrecognized behavior patterns or traits.

Blurred spots: Some feedback helped participants clarify traits they had been vaguely aware of but had not fully acknowledged. When counterparts reiterated things participants had heard before, it brought overlooked behaviors and habits back into focus. P4 noted, *"A lot of the feedback was familiar; I'd heard similar things before, including from a counselor. But when P3 brought it up again, it really resonated with me,"* illustrating how repeated feedback reinforced her self-awareness. Similarly, other participants found that having their known weaknesses pointed out again gave them the push they needed to address those issues. P12 mentioned, *"It was a flaw I was already aware of, but hearing it from P11 again made me more vigilant and motivated to change,"* showing how the feedback encouraged action.

Reflected self: The feedback allowed participants to see themselves through the eyes of others, providing insight into how they are perceived and the impact of their behaviors. For instance, P12 believed he was organized, but when his counterpart expressed dissatisfaction, he became aware of the expectations others had of him. Some participants noted a mismatch between their self-image and how others viewed them. P14 learned that others saw him as responsible and efficient, even though he personally felt he had many shortcomings. P2 shared, *"I was surprised when P1 praised something I thought was a weakness. It made me realize others perceive it differently."* These reflections prompted participants to reconsider their self-perception and assess how their behaviors might align—or conflict—with the expectations of others.

4.2.3 Gaining Self-Awareness by Observing Others. Observers did not only just learn about their counterparts during the observation process but also gained insights into themselves. By comparing their behaviors with those of their counterparts, participants found inspiration, developed empathy, and became more self-aware. For instance, P14 admired P13's dedication to hobbies, starting, *"P13 immerses herself in webtoons with depth, which inspires me to develop a more meaningful hobby."* Similarly, P13 reflected on her own shortcomings, admitting, *"I'm not great at expressing emotions, but seeing how naturally P14 does it made me want to improve."* These reflections often led to tangible changes. P16, for instance, noted, *"After observing how P15 interacted with his mother, I realized I was distant with mine, so I've made an effort to be warmer to my mom."* In addition to drawing inspiration from their counterparts, participants also realized that their own values and interests shaped the way they observed others. Initially focused on visible actions, their attention shifted towards qualities that aligned with their own aspirations or highlighted personal deficiencies. As a result, these observations became more prominent in their records. For example, P2 noted that she increasingly focused on traits she valued or lacked, gaining insight into what mattered most to her. Participants tended to focus their observation journals on these areas, even while observing a wide range of behaviors.

4.3 Understanding How Feedback Was Shaped and Received

4.3.1 Characteristics of Feedback. A key characteristic of the feedback provided by observers was its contextualized nature. Since participants were paired with peers who knew each other well, the feedback was highly personalized and tailored to the specific circumstances and environments. Observers, familiar with the nuances of their counterpart's situation, offered concrete solutions or advice that reflected individual characteristics and preferences. For example, P16 complimented P15 on how good he looked in hats and, knowing P15 often rides a scooter, suggested wearing the hat backward while riding to prevent it from blowing off. When pairs shared common goals or experiences, they frequently proposed activities they could do together. In crafting this feedback, participants often filtered their observations to focus on aspects they believed would be most helpful to their counterparts. While they made numerous observations, they excluded details unlikely to provide constructive feedback or considered overly personal, particularly if they thought such observations might make their counterparts feel uncomfortable. For example, P2 explained, *"There were behaviors I found interesting, but I intentionally didn't write them down because I felt my counterpart might think she was being observed too closely."*

In addition to contextualization, participants took great care in crafting their feedback, mindful of the potential for misinterpretation or emotional impact. Despite close relationships, they were aware that written feedback lacked nonverbal cues, which can lead to misunderstanding. To address these concerns, participants were cautious with critical feedback, revising their comments to ensure clarity and avoid harm. They used strategies like positive language or framing feedback in a hopeful tone. For instance, P9, noticing P10's stress, instead of saying, *"Sitting at your desk worrying won't solve anything,"* suggested, *"Let's go for a walk to get some stress out."* They also provided context and examples, balanced criticism with praise, and structured their feedback logically to prevent overwhelming their counterparts. However, when these strategies were not applied, challenges emerged. For example, P5's softened feedback still came across as too harsh to P6. As P6 described, *"The feedback felt too definitive and lacked positive reinforcement, impacting my self-esteem."* P5, in hindsight, regretted not delivering more balanced feedback sooner. These cases highlight the importance of thoughtful, balanced, and contextually appropriate feedback, as missteps can damage motivation and self-esteem.

4.3.2 Reception of feedback. We analyzed the reflection cards to understand how participants received and acted upon feedback from their counterparts. Most participants responded positively, with praise boosting their confidence and motivating them to further enhance their strength. Feedback that suggested areas for improvement was often met with an active effort to follow the recommended strategies. For example, P8 installed a diet management app recommended by P7 and used it consistently to support his weight loss journey. Participants appreciated the thoughtfulness behind the feedback and reported satisfaction when creative solutions were offered.

However, not all feedback was accepted without modification. Some participants adapted suggestions to better fit their own circumstances or chose not to act on suggestions they found unnecessary. In some cases, participants struggled to take suggested action because of decreased self-efficacy from previous challenges. For instance, P11 received advice from P12 to reduce smartphone usage to improve sleep hygiene, but noted the challenge due to previous unsuccessful attempts. In such cases, participants often documented in the response note of their reflection card why certain suggestions would be difficult to implement and expressed a willingness to find alternatives. Additionally, when participants believed feedback could also benefit the observer, they sometimes recommended that the observer try it as well.

4.3.3 The Role of Reciprocity in Feedback Dynamics. The reciprocal nature of the process motivated participants to explore new areas of observation and expand their scope of inquiry. P18 commented, *"Seeing my partner's feedback made me realize that there were aspects of behavior I hadn't thought to observe. Next time, I should pay attention to those as well."* This exchange not only provided new insights to both participants but also influenced their future observations and feedback. As a result, when participants later documented their observations in the analysis card, their feedback became more diverse and thoughtful, incorporating aspects they had previously overlooked.

Participants also highlighted the importance of reviewing their counterparts' responses to their feedback, noting that this practice shaped future actions and reduced anxiety about how their comments were received. P2 mentioned, *"I was really curious about* *how my feedback would be received. But being able to see their reaction, rather than just ending with the feedback, helped me decide how to approach my next feedback."* Experiencing their feedback being well-received or acted upon created a sense of fulfillment, reinforcing their motivation to provide more thoughtful and constructive feedback over time. Participants also recognized the effort involved in creating detailed observations, which fostered a sense of responsibility and deepened their engagement. This dynamic underscores the significance of reciprocity in cultivating meaningful engagement and sustaining positive feedback cycles.

4.4 Exploring the Relational Dynamics of Reciprocal Tracking

4.4.1 Fostering Social Connection Through Reciprocal Tracking. Participants reported experiencing deeper conversations and increased joint activities, potentially facilitated by the structured feedback process. P7 noted, *"This experiment gave us more to talk about, and we found more everyday fun, like exercising together or making plans,"* highlighting how shared activities enriched their interactions. Similarly, P16 observed, *"We ended up discussing habits that we usually just brush off,"* highlighting how structured feedback encouraged conversations about previously overlooked topics. These observations suggest that reciprocal tracking may foster curiosity and open communication, leading to more meaningful interactions. Additionally, some participants indicated that the experiment allowed them to address issues they typically avoided, leading to strengthened bonds. P12 noted that after sharing data about a broken dish incident at home, he felt compelled to apologize again to P11, adding, *"This experiment allowed us to address things we wouldn't normally talk about, making our relationship healthier."*

4.4.2 Navigating Challenges in Trust and Feedback: Insights from a Dropout Case. The dropout case of P5 and P6 highlighted the potential relational and emotional complexities of reciprocal tracking when trust and effective communication are lacking. Despite their long-standing relationship, unresolved tensions from the past made it difficult for them to interpret and accept negative feedback constructively. Both participants entered the process with good intentions, aiming to provide helpful insights. However, P6 noted, *"It felt like P5 doesn't take me seriously,"* illustrating how perceived dismissiveness led to a growing sense of mistrust. Compounding these challenges was the limited time available to process feedback and manage emotional responses. P5 admitted, *"Receiving negative feedback hit me harder than I expected,"* reflecting the emotional strain caused by insufficient time to internalize and reflect on the comments. The lack of adequate strategies for delivering sensitive feedback further exacerbated these issues. Feedback that was meant to be constructive was perceived as overly critical, leading to misunderstandings and a breakdown in communication. This case underscores the relational and emotional challenges that can emerge in reciprocal tracking when participants struggle to align their expectations or navigate sensitive feedback exchanges.

5 Discussions

In this section, we discuss how reciprocal tracking augmented personal informatics through the core benefits identified in the Peerspective study. We also examine the challenges of incorporating social dynamics into reciprocal tracking, including emotional burden and privacy concerns, and propose design considerations to support effective and sustainable reciprocal tracking systems.

5.1 Integrating Reciprocal Tracking into Personal Informatics Systems

Our findings highlight how reciprocal tracking can enhance the reflective capabilities of personal informatics systems through mutual observation and data sharing. In our Peerspective study, participants reported gaining new perspectives through peer feedback and regular observations. This iterative observation process not only sparked curiosity about each other but also acted as a mirror, prompting participants to reflect on their own behaviors and thought processes in meaningful ways. These findings align with prior research showing that observation can simultaneously deepen self-awareness and foster reflective thinking [4, 5]. Furthermore, these insights resonate with Rapp and Boldi's critique that existing personal informatics systems often focus narrowly on isolated actions while overlooking the broader life contexts and subjective experiences that lend those actions meaning [84]. Their existential model of behavior emphasizes the value of systems that engage with the personal and contextual dimensions of users' lived experiences [83]. The Peerspective study offers a way to address this gap by creating opportunities for participants to connect their observations to their everyday lives, encouraging more nuanced and context-aware reflections. By fostering shared experiences and mutual reflection without relying on traditional self-tracking tools, it provided participants with a way to explore behaviors within their unique life contexts. This approach presents a promising framework for enriching the self-tracking process and broadening the scope of personal informatics systems.

Another critical aspect of reciprocal tracking lies in its potential to address challenges during the preparation stage of the PI process. Li et al. identify this stage as a critical moment when users set objectives and determine which behaviors to track [49]. However, many users face challenges in identifying meaningful data or defining actionable goals, often leading to frustration or disengagement [88]. Our Peerspective study introduces peer-driven observations that help uncover blind spots—behaviors or patterns individuals might struggle to notice on their own. Participants in our study used these insights to contextualize their actions within broader patterns and align their tracking goals with their personal circumstances. This approach helped users establish clearer and more actionable objectives, reducing the initial barriers to self-tracking and enhancing the preparation stage of the PI process.

Reciprocal tracking not only supports users in setting meaningful objectives during the preparation stage of the PI process but may also extend to the lapse stage, as described by Epstein et al. [26], where users often disengage. This stage occurs when users lose motivation or disengage from tracking, often due to monotony or a lack of perceived benefits [18, 23, 46]. Epstein's study highlights that disengagement can occur when the insights gained from tracking become repetitive or fail to provide new perspectives, leading users to lose interest in the process. The Peerspective study suggests a complementary perspective that could be valuable during this stage by introducing fresh interpretations through peer feedback. In our study, participants described how peer observations brought new insights into their past behaviors, uncovering dimensions they had not previously considered. Beyond identifying blind spots, participants also clarified blurred spots—traits they had vaguely noticed but had not fully acknowledged. While our study did not observe instances of lapse, this reflective process has the potential to transform the lapse stage from a point of frustration into an opportunity for rediscovery, motivating users to revisit their actions with renewed clarity and motivation [3].

While reciprocal tracking offers significant benefits, its implementation presents both practical and emotional challenges. Our study required participants to document observations daily and exchange data regularly. While this structured approach ensured consistency, it may have increased cognitive and relational burdens, raising concerns about feasibility and sustainability in everyday contexts. Maintaining high-quality feedback over time can be demanding, as it requires sustained effort in both observation and articulation. Prior research highlights that overly rigid tracking systems risk discouraging engagement [46, 80, 85]. To address these concerns, future applications of reciprocal tracking should explore more flexible participation models. Rather than restricting its use to specific stages, adaptive engagement strategies could better accommodate the dynamic nature of personal informatics. One approach is to begin with frequent tracking and gradually transition to periodic engagement (e.g., weekly or monthly) to balance reflection with reduced burden. Another possibility is to develop systems that detect significant life changes, such as shifts in routines or emerging self-tracking needs, and prompt engagement when relevant. Since lapses in tracking often occur in the absence of new tracking needs, self-learning opportunities, or situational changes [26, 56], intelligent detection mechanisms could help users reconnect with tracking at meaningful moments. By acknowledging the limitations of a structured approach while emphasizing the potential for adaptable, temporally distributed participation, reciprocal tracking can better integrate into long-term personal informatics practices.

5.2 Tailored Feedback through Enhanced Understanding in Reciprocal Tracking

The Peerspective study enables participants to provide feedback that is not only personalized but also deeply contextualized by leveraging their mental models of their peers. In our study, participants relied on their existing personal knowledge to observe behaviors and infer motivations or causes behind actions. This approach allowed them to go beyond surface-level observations, offering insights that accounted for the recipient's specific context. These tailored feedback sessions often included actionable suggestions aligned with the recipient's circumstances, making the feedback more relevant and acceptable. While these observations were subjective and occasionally inaccurate, they encouraged deeper reflection by drawing connections between behaviors and their potential causes. This stands in contrast to previous research in personal informatics, which has primarily focused on identifying correlations within self-tracking data [7, 12, 13, 52, 82]. Jung et al. emphasize the importance of identifying causal factors to uncover how behaviors, environments, and emotions interact, fostering meaningful reflection and behavior change [41]. Although the feedback in our study did not establish authentic causality, the participants' educated guesses leveraged their contextual understanding to offer reflections that are often difficult to achieve through self-tracking alone.

Despite these advantages, participants often grappled with the uncertainty of whether their feedback was meaningful or helpful to their peers. This concern reflects a broader challenge in integrating social aspects into personal informatics, where users may doubt whether shared data or insights hold value for others [16, 25, 56]. In our study, this uncertainty was mitigated when participants received responses indicating that their feedback had been useful or had led to action. Such positive reactions validated their contributions, fostering mutual trust and motivating them to invest more effort in providing meaningful and contextually rich feedback. As participants observed how their counterparts engaged with their feedback and found it useful, they gained confidence in their ability to provide relevant insights, reinforcing the trust and sustained engagement between peers [74]. This process not only enhanced participants' engagement but also refined their mental models, enabling them to provide more nuanced and tailored advice over time. A well-designed feedback loop is therefore critical for sustaining reciprocal tracking. By allowing contributors to see how their input is received and utilized, systems can foster trust and mutual accountability while encouraging more meaningful exchanges. Over time, these interactions help participants refine their mental models of peers by observing new behaviors and uncovering previously unnoticed patterns or connections. Building on prior findings in collaborative goal setting [2], the Peerspective study enables participants to filter out irrelevant information, prioritize critical issues, and distill complex observations into actionable advice, while adapting feedback to evolving circumstances.

Effective feedback loops should carefully balance the need for timely interaction with the emotional and cognitive demands of participants. Insights from a dropout case revealed that participants sometimes felt emotionally burdened by feedback that provoked negative reactions, particularly when they lacked sufficient time to process or respond thoughtfully. Short response windows occasionally forced participants to provide insincere or incomplete reactions, exacerbating misunderstandings and straining relationships. To address these challenges, feedback systems should incorporate flexibility, allowing recipients enough time to reflect before responding. By tailoring the pacing and structure of feedback interactions to the relational dynamics between participants, systems can better accommodate varying needs and preferences. This emphasis on emotional well-being and thoughtful engagement helps reciprocal tracking systems maintain trust and foster positive, sustainable interactions.

5.3 Navigating Social Dynamics in Reciprocal Tracking

The Peerspective study had a profound impact on participants' social relationships, yielding both positive and challenging outcomes. On the positive side, the process fostered increased interaction and deeper communication between peers. By engaging in joint activities and exchanging detailed feedback, participants explored topics rarely discussed in their usual interactions, strengthening their bonds and enhancing mutual trust. Many participants expressed a heightened sense of responsibility toward their peers, acknowledging the effort invested in providing feedback. This mutual accountability not only deepened engagement but also encouraged more thoughtful and tailored contributions, creating a dynamic of reciprocal reinforcement. However, the process was not without its difficulties. Dropout case in the study highlighted that tensions could arise from misaligned expectations about feedback or observation styles, leading to emotional strain. Additionally, participants noted that the intensity of observation, while well-intentioned, occasionally led to discomfort or privacy concerns. These insights underscore the need for careful consideration of relational dynamics in designing reciprocal tracking systems.

To address these challenges, a well-structured onboarding process is essential. Establishing clear expectations at the outset helps align participants' goals and boundaries, reducing misunderstandings or discomfort. For instance, participants should discuss the type of data they wish to track, the depth of feedback they expect, and what behaviors are off-limits for observation. Furthermore, onboarding should not be a one-time event, as relationships and individual needs evolve over time [71]. Systems should be flexible enough to adapt to these changes, ensuring that initial expectations remain relevant as circumstances shift [90]. Regular check-ins during the tracking process can help reassess mutual goals and maintain alignment, ensuring the system remains supportive and constructive. This iterative approach fosters trust and adaptability, enabling participants to navigate the complexities of reciprocal tracking with greater ease and confidence.

Another critical aspect is ensuring that feedback is balanced and constructive to minimize emotional strain. Differences in perspectives during tracking and interpretation can lead to misunderstandings [45, 66] or feelings of compromised autonomy [71, 95]. Even well-intentioned feedback can sometimes be overly definitive or delivered in a tone that feels dismissive or harsh, leading to negative emotions and tension, as seen in the dropout case. Participants emphasized the importance of adopting a considerate and balanced tone when providing feedback, ensuring it feels supportive and aligns with the recipient's capacity to engage with both strengths and constructive suggestions. Systems could support this by integrating technical aids such as Large Language Models (LLMs), which refine feedback by identifying problematic language and suggesting constructive alternatives [9, 106]. For example, LLMs could flag overly critical phrasing and propose revisions that maintain a positive tone. Retrieval-Augmented Generation (RAG) [111] could further enhance personalization by referencing previous interactions, ensuring relevance and alignment with recipient preferences. At the same time, systems should support recipients by helping them understand that the feedback is inherently subjective and may include gaps or misunderstandings. Guiding recipients to view feedback in a broader context, considering their own strengths alongside the feedback, can promote a more holistic and balanced reflection.

6 Limitations and Future Work

This study presents several limitations that warrant further exploration. First, the one-week duration of our study provided valuable initial insights into how participants engaged with reciprocal tracking and reflected on their behaviors. However, some participants reported reaching a point of tracking saturation, where observations began to feel repetitive. This suggests that while longer-term studies could reveal additional benefits, such as deeper self-understanding, they might also introduce new challenges, including declining motivation and heightening privacy concerns over time [10]. As prior research highlights, continuous tracking is not always necessary or beneficial [26, 93]. Future studies could investigate alternative approaches, such as periodic engagement or flexible tracking schedules, to balance the reflective benefits of reciprocal tracking with the need to prevent fatigue and sustain motivation over time.

Second, although the high-quality and personalized feedback in this study was a key strength, it also raises concerns about scalability. Crafting thoughtful feedback requires significant effort, which may not be feasible for everyday use. To reduce this burden, future research could explore methods such as structured templates, optional quantitative metrics, or semi-automated suggestions to streamline the feedback process while preserving its interpersonal value [11]. Scalable data can be recorded and shared using quantitative metrics, and peers can make comments about the quantitative data by providing contextually rich data to the numerical representation [35]. However, simplifying feedback risks losing the nuanced, supportive exchanges central to reciprocal tracking. Striking a balance between scalability and relational quality remains a challenge, suggesting that reciprocal tracking might be most effective when applied selectively in contexts where deep reflection and feedback are most needed.

Third, as this study was conducted in South Korea, cultural factors may have influenced participants' openness to data sharing and feedback. Eastern cultures often emphasize sharing personal data with close connections to foster social support, while Western cultures prioritize privacy and are more cautious with data sharing [55, 75]. Future research should examine how reciprocal tracking systems can adapt to diverse cultural norms, ensuring their relevance across varying contexts.

Finally, the study's participant group consisted of a relatively small and younger population, which may have shaped the findings. Given that reciprocal tracking likely depends on relationship dynamics and social contexts, further studies with more diverse and larger samples are necessary to understand how these factors impact its practice and outcomes.

7 Conclusion

This paper explored the potential of reciprocal tracking in uncovering personal blind spots and enhancing self-understanding through mutual observation and feedback. We presented Peerspective study, an approach in which pairs of peers observe and reflect on each other's feedback. By incorporating peer perspectives, the study demonstrated the value of reciprocal tracking as a complement to existing personal informatics systems. The study revealed that peer feedback expanded participants' self-concept by revealing unnoticed behaviors and encouraging reflection through observing others. Furthermore, engagement with tracking increased, driven by a sense of mutual responsibility and the desire to provide meaningful support, which strengthened interpersonal relationships. We identified design opportunities for effective and sustainable reciprocal tracking systems, including onboarding processes to align participants' expectations and feedback mechanisms that balance critique with empathy. We hope this work will inform the design of future personal informatics tools engaging with reciprocal interactions in everyday contexts.

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