Visualizing Uncertainty in Multi-Source Mental Health Data

Michael Hoefer
michael.hoefer@colorado.edu
University of Colorado Boulder
Boulder, Colorado, USA

Bryce Schumacher
bryce.schumacher@colorado.edu
University of Colorado Boulder
Boulder, Colorado, USA

Danielle Albers Szafir
danielle.szafir@cs.unc.edu
University of North Carolina-Chapel Hill
Chapel Hill, North Carolina, USA

Stephen Voida
svoida@colorado.edu
University of Colorado Boulder
Boulder, Colorado, USA

ABSTRACT

Self-tracking technologies, especially those facilitating support from social systems, are becoming more common for treating serious mental illnesses in both clinical and informal contexts. A recently proposed feature is *co-tracking*, where data is gathered not only from the perspective of the user managing their condition, but also from their close contacts. The proposed system therefore supports multiple perspectives (data streams) about the same variable of interest (i.e., an individual's mood). However, the subjective and reciprocal nature of mental health data gives rise to challenges in visualizing uncertainty that must be addressed before clinical use. Here, we create an application-specific typology of uncertainty for visualizing multi-source mental health data, and propose design solutions to communicate this uncertainty. Via a case study of mood tracking with bipolar disorder, we present an interactive visualization prototype for understanding dynamic mood states in close relationships, moving toward a real-world implementation of a co-tracking informatics system.

CCS CONCEPTS

• **Human-centered computing** → **Information visualization**; **Visualization theory, concepts and paradigms**; **Visualization systems and tools**; • **Applied computing** → **Health informatics**.

KEYWORDS

personal informatics, mental health informatics, information visualization, mental health data, visualizing uncertainty, co-tracking, person perception, quantified self, bipolar disorder

1 INTRODUCTION

Millions of individuals suffer from serious mental illnesses (SMI), such as bipolar disorder, PTSD, and major depressive disorder. These illnesses are estimated to cost over $200 billion annually in health care treatment costs, loss of earnings, and disability benefits in the United States alone [14]. Globally, the direct and indirect impact of mental disorders is estimated to be $2.5 trillion annually [39]. The use of self-tracking technology is a growing strategy for treating SMI, and various self-tracking applications have been developed for use in both informal and clinical contexts [25, 33]. Self-tracking in a mental health context involves directly tracking affective variables, such as experienced emotions and mood, as well as behavioral proxies such as sleep and exercise [15]. Bipolar disorder (BD) presents a particularly compelling case for self-tracking, given its chronic nature and the importance of stabilizing mood and various social rhythms for long-term condition management [6].

The primary symptomology of concern in BD is the extreme fluctuations in mood state, as individuals move between euthymia (steady state), depression (low mood), hypo-mania (rising mood), and mania (elevated mood). Individuals with BD are more likely to commit suicide than any other SMI cohort—approximately 1 in 5 individuals with BD die from suicide [1]. Treatment with medication is often augmented with family-focused therapy [23], leveraging psychoeducational training among both the individual with bipolar disorder and their caregivers, or interpersonal and social rhythm therapy (IPSRT), which involves tracking mood and the timing and routine-ness of key social interactions [6].

Both homegrown [20] and formalized [7] self-tracking systems have been developed to support interpersonal social rhythm therapy (IPSRT) for individuals with BD. The present work builds on a series of multi-stakeholder design activities for the development of a flexible self-tracking app that facilitates interpersonal ecologies necessary for relational recovery in BD. Prior studies explored the use of self-tracking with individuals managing BD [20], visualizations of the lived experience of BD [36], issues of privacy and data sharing [32], and design considerations for supporting social ecologies of an individual's social support system [25]. Most recently, a study was conducted with mental health clinicians to understand how social self-tracking interfaces can be integrated with professional mental health care [9].

Of the nine designs presented to clinicians in this most recent study [9], two were considered to be the most novel and potentially therapeutic for long-term management of bipolar disorder. The first is *data commenting*, which allows for individuals to comment

about data they or someone else collect. The other is *co-tracking*, where a close relation tracks information on behalf of the individual in question, from their own perspective. Clinicians highlighted the usefulness of co-tracking to provide "another perspective" on someone's mood state [9], which might help identify important changes that the individual is unaware of or is choosing not to track.

In addition to providing useful information on mental states to a clinician, co-tracking is expected to benefit those gathering the data. By directing attention towards the mood of others, and creating new feedback loops in dyadic emotional systems, co-tracking may improve empathic accuracy (EA), the extent to which one can accurately infer another's thoughts and feelings [13]. EA has been shown to increase the level of "invisible support" (without recipient awareness) in partnerships, which is known to be especially helpful for overcoming challenges [10]. We therefore suggest two primary goals in designing a visualization for a co-tracking informatics system:

(1) **Provide clinicians with a multi-source representation of an individual's mental health indicators**
(2) **Facilitate improved empathic accuracy—and therefore social support—within close personal relationships, themselves**

The ephemeral and subjective nature of mental health variables, such as mood and experienced emotions, combined with uncertainty inherent in interpersonal perception, create a variety of data visualization challenges. In the remainder of the paper, we briefly review related work in visualizing self-tracked mental health data, then present design requirements for a co-tracking visualization based on a typology of sources of uncertainty arising from multi-source mental health data streams.

1.1 Statement of Contributions

In this work, we explore the design challenges for creating a visualization of multi-source mental health data. Motivated by the challenges of BD, where self-tracking in a social context can support relational recovery, we synthesize a series of design requirements, and implement a prototype web-based visual analytics solution[1] using D^3[2]. We frame the visualization challenges around an existing typology of uncertainty [38] and suggest methods for visualizing uncertainty for each type (summary in Table 1). The design considerations presented in this paper can be applied to a variety of mental health data visualizations for use in both informal and clinical contexts, and will hopefully spur further research in multi-source mental health data applications.

2 RELATED WORK

Previously developed personal informatics systems have incorporated visualizations to help users better understand and learn from their self-tracked data, intended to be used during reflection [18]. The study and development of these visualizations is known as personal visualization and personal visual analytics [11]. The most common personal analytics systems focus on objective data such as food, physical activity, or physiological states (heart rate, for

example) and tend to utilize time-series graphs to help users identify patterns and changes in their data over time [26]. While some applications enable users to develop their own visualizations [16], another study found that users spend the majority of time viewing and interacting with system default visualizations [37], motivating careful design specific to the intended use case.

A variety of mental health-focused systems have been designed to track subjective data like mood and include visualizations utilizing lists, graphs, and aggregations into pie charts [3]. The MoodMap application is focused on improving mood awareness, and seeks to visualize a mood in the context of a two-dimensional feature space [24]. MobiMood is a social mood app that enables the sharing and commenting on the mood of others [4]. However, there is currently no work reporting on a system that supports the tracking and visualization of multi-source (co-tracked) mental health data, nor the challenges that arise when visualizing such data.

The subjective nature of mental health data, and presence of indirect qualitative uncertainty [29], motivates an exploration of the various ways that uncertainty enters the data stream. Although visualizing uncertainty is relatively uncommon in current practice, doing so can help users gain more insight into the data-generating processes [12], which, in this case, is a process of significant concern: how an affective state is experienced. Prior research on visualizing uncertainty has been conducted in more objective domains such as fluid flow [19], environmental vector fields [40], and visualizing surfaces [8]. More generally, previous work has resulted in a typology of sources of uncertainty that can be applied to multiple domains [38], as well as suggestions for communicating uncertainty in visualizations [28, 30].

3 CO-TRACKING SYSTEM DESIGN FOR UNCERTAINTY

In this section, we detail a use case for the proposed co-tracking system for an individual managing bipolar disorder, followed by an elicitation and embodiment of design requirements in a prototype analytics system. Along the way, we construct an application-specific typology for uncertainty in visualization of multi-source mental health data. For brevity, we present the sources of uncertainty, design requirements, and corresponding prototype features in an integrated fashion.

## 3.1 The Use Case of Co-Tracking for Bipolar Disorder

The proposed co-tracking system was conceptualized after discussions with mental health clinicians about managing BD. As such, the intended users of the system are individuals managing type I or type II bipolar disorder, one or more members of their social support system, and their mental health care providers. Individuals managing BD can use the system to track their mood on a scale of -3 to +3 (similar to the scale used in [21]), as well as their perception of the mood of their "co-tracker" (a close relation in their support system, such as a spouse or parent). In addition, this co-tracker records their own mood, as well as their perception of the mood of the individual managing bipolar disorder. In both cases (for the self and for the "other"), mood is tracked using an interface such as the prototype shown in Figure 1. Therefore, there are two data

Table 1: Sources and visualization of uncertainty in multi-source mental health data (types from [38])

Uncertainty type	Source of uncertainty	Emergent visualization design recommendation
Accuracy & Error	Psychological projection	Encode both raters' emotions
Precision	Reduction of complex emotional data	Augment with qualitative context
Completeness	Data not collected or not shared	Differentiate reasons for "missing" data
Consistency	Perceived mood vs. experienced mood	Display co-tracked ratings side-by-side
Lineage	Variability in time spent together	Encode level of contact
Currency and Timing	Delays between experienced and reported perception	Communicate an estimate of time delay

streams (self-tracked and co-tracked) about each of the two primary variables the visualization seeks to represent (the mood of the two individuals in the dyad).
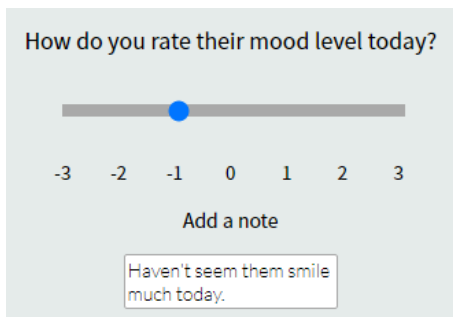
Figure 1: Proposed interface for collecting multi-source mood data

The individual managing BD can then bring these visualizations into a clinical setting with their mental health care provider to help communicate multiple perspectives of how they are doing and provide clinicians more "in the wild" information with which to manage medication and other forms of treatment. Outside of a clinical setting, a visualization of these data streams is intended to facilitate reflection and improved self-knowledge about the dynamics of their emotional systems. For example, individuals could learn how their mood correlates with their co-tracker's mood, as well as how their mood is "coming across" to their co-tacker. In addition, the individual can learn how accurate they are at perceiving the mood of their co-tracker, leading to improvements in empathic accuracy, and therefore relationship outcomes [13].

To support the development of the visualization for our prototype system, we created four synthetic datastreams, representing data collected within two co-tracking partnerships over a period of time (in this case, three weeks). These synthetic datastreams included self-tracked mood of each individual and co-tracked mood of their perception of their partner's mood, with one rating in each of these categories per day. In order to simulate expected privacy management practices (after [32]), some ratings were selected to be un-shared with the partner. In order to simulate expected lapses in tracking, some days were randomly selected to have no tracked data. Therefore there are two reasons why data may be missing.

3.2 Design Requirements

Given the novelty of a co-tracking application, where two individuals are providing ratings of each other's mood, we turn to basic research in psychology, as well as results of discussions with clinicians in the literature [9] to identify the design requirements of a visualization supporting multi-source mental health data.

Psychologists have long studied phenomena involving interpersonal perception [17], including evaluations of mood in partnerships. A common methodological approach used in interpersonal psychology studies is to utilize daily diaries and surveys within partnerships, having each partner record their own mood and their perception of their partner's mood [35]. Our proposed system modernizes this data collection strategy with a mobile application where users can log both their mood, as well as their perception of one another's mood (see Figure 1).

As the "ground truth" of an individual's mood is perhaps only known by that individual, an outsider's perspective is subject to a variety of biases that create uncertainty of empathic accuracy in the data stream. To structure our discussion on uncertainty in mental health data, we draw a subset from the typology created by Thomson et al. [38], given its flexibility in adoption to new visualization domains and focus on human-generated data, and describe how a subset of the sources of uncertainty appear in multi-source mental health data streams (not all sources were discovered in this application). We treat previous studies in psychology (specifically, interpersonal perception) as a source of "expert knowledge" that we use to pre-emptively capture implicit error and shape requirements that can help externalize this error [22]. Emergent design requirements are emphasized in bold in the following sections and summarized in Table 1.

3.2.1 Accuracy and Error. Accuracy uncertainty is described as a "difference between observation and reality" [38]. While the individual's self-rating can be considered a type of "reality," their co-tracker's perception will include error due to known psychological mechanisms. Projection, or bias, is when one individual thinks another's mood state is similar to their own, and can be a significant source of inaccuracy in emotional perception, particularly when partners do not share common environmental stimuli [5].

While a co-tracking system may, over time, train users to become more accurate in their perception of their partner's mental states via new feedback loops, the system should communicate this source of uncertainty by **including a representation of the co-tracker's own mental state in the visualization**. To support this, the prototype system allows for individuals to toggle each of
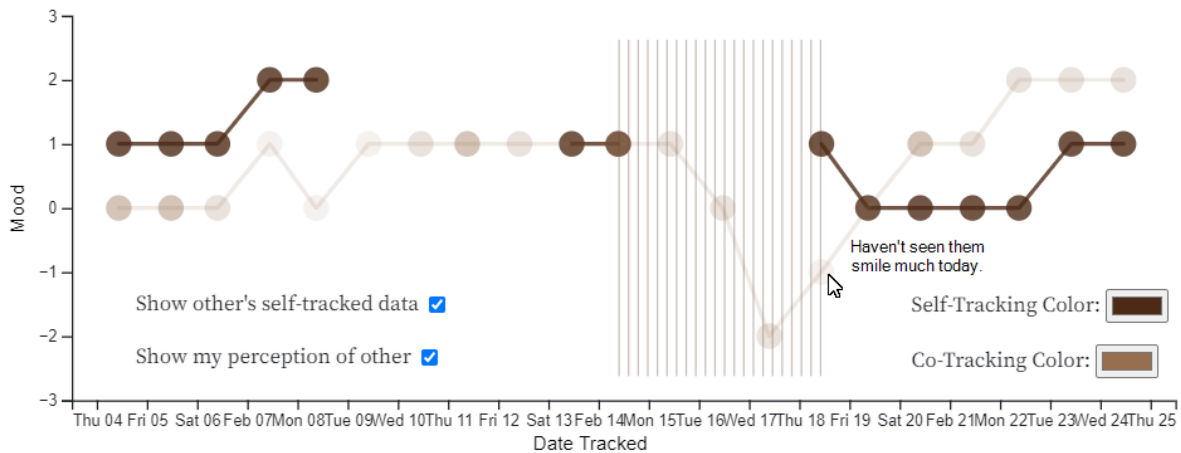
Figure 2: A prototype co-tracking visualization embodying requirements for communicating uncertainty

the four data streams (my self-tracked mood, your self-tracked mood, my perception of your mood, your perception of my mood), to clearly show projection effects in mood ratings (Figure 2). However, overlaying these multiple streams of data on a single graph results in visualization complexity that may be difficult for some users to effectively "read." To reduce this clutter, future work might explore and evaluate encoding some of these streams (e.g., the co-tracker's mental state) as a linearly valenced emoji in place of an additional series of circular glyphs.

3.2.2 Precision. Precision is the "exactness of measurement" [38] and is largely a function of the informatics system used to gather the data. Traditional mood ratings for managing BD rely on discrete numeric scales with a value of zero representing a neutral mood state [21]. This approach requires that users aggregate rich interpersonal experiences into single numeric values, resulting in a simple, coarse-grained representation of an otherwise complex phenomenon (affective state). While clinicians noted the importance of these standard numeric scales for informing medication changes, they also desired additional information about the context in which the ratings were made [9].

We therefore suggest that a co-tracking system (similar to other emotion tracking systems [3]) should **accommodate qualitative contextual information alongside numeric ratings**, allowing for increased precision of mental health representations.

Our prototype visualization supports additional context via the *data commenting* feature: users can hover over particular data points, which reveals a tooltip showing any annotations provided by the user when they recorded a particular numeric mood rating. We intentionally enlarged the data points to accommodate potential hand-tremors, a common symptom of individuals taking lithium for BD [21].

Combining contextual data comments with a time-series graph of mood state provides a narrative element to the visualization, which is often lacking in personal informatics systems [34].

3.2.3 Completeness. Data sharing and privacy was a noted concern in previous empirical studies with individuals suffering from

SMI [32]. Given the potentially sensitive nature of one's mood, individuals should be able to selectively share mood data on some days and not on others. An individual may not have access to the complete mood datastream of their partner for two reasons. First, the individual may not have tracked their mood for a particular day, especially if the individual is in an extreme mood state [21]. Second, the individual may have chosen to not share their mood state on a particular day. This creates a new challenge for data representation, as there are two different reasons why data may be incomplete. Clinicians highlighted that when an individual chooses not to share a self-tracked mood, this could be therapeutically relevant and might prompt useful conversations ("*why didn't you want to share your mood with me?*") [9]. Therefore, the visualization should **clearly communicate the reason for missing data** in a mental health data stream.

To support communicating this distinction, the visualization includes two different encodings for these sources of incompleteness. For un-tracked data, the mood line is discontinuous, indicating that no data was collected. For data that is not shared, a vertical line shading is overlaid on the plot. The added geometry [30] spans the majority of the y axis, indicating that the actual mood value could be anywhere within the range. Figure 2 shows a co-tracking visualization where data is both missing (discontinuous line) and not shared (shaded region), perhaps because of a dip in mood state—both behaviors that might be clinically relevant.

3.2.4 Consistency. Consistency is the "extent to which info components agree" [38]. A co-tracking system has two primary information components informing the same variable: the individual's self-tracked mood, and their co-tracker's perception of that mood. The level of (dis)agreement between these two perspectives will likely vary from dyad to dyad, as well as temporally within a dyad. Communicating changes in this consistency to clinicians is one of the motivating factors in creating a co-tracking system, which necessitates a requirement that the visualization clearly **display the individual's self-rating alongside (or in the context of) their co-tracker's rating of them**.

To allow people to compare data across these streams, our design visually couples the self-tracked and co-tracked rating about each person's mood using color, to highlight the level of consistency between the two ratings.

3.2.5 Lineage. Lineage is the "conduit through which information is passed" [38]. Verbal and non-verbal communication between individuals, along with shared environmental stimuli, create a "lineage" by which affective state is transmitted. Psychologists have determined that levels of partner expressiveness [27] and the presence of conflict [35] both influence this lineage. In addition, the amount of contact two individuals have would also mediate the degree to which they can accurately perceive one another's emotional state. A co-tracking visualization should therefore **communicate an estimate of how much affective information an individual might have received about the other** before providing the co-tracked rating.

Given that the partner's perception (the co-tracked data) is subject to biases and is further from the actual experience of the mood state, the visualization decreases the opacity of the co-tracked data as compared to the self-tracked data (Figure 2). The opacity is based on the level of contact the two individuals had throughout the day (e.g., determined via location fingerprinting, communication logs, or self-report), and therefore communicates the **lineage** of affective information. Highly faded nodes represent ratings where the co-tracker had very little contact with the individual whose mood they rated. Self-tracked mood is considered to be the "ground truth" and is therefore displayed with maximum opacity.

3.2.6 Currency and Timing. Timing between the observations made by individuals and the actual reporting of the mood rating can lead to additional uncertainty in the data. When asking an individual to report on how they felt over the course of the day (as opposed to how they feel in a single particular moment), the individual must perform some averaging process to report their aggregate mood [31], which then becomes subject to the experienced mood biases mentioned before. These same effects are present when retrospectively reporting on a perceived mood state of another individual. Therefore, a co-tracking visualization should clearly **indicate the time lag between the experienced (or perceived) emotional state, and the rating of the emotional state**. While the synthetic data assumes tracking occurred at the same time every day, the X-axis on the prototype visualization indicates the time of report and could therefore highlight lagging reports within a day.

Timing uncertainties might also be mitigated at the point of data collection through the use of notifications or prompts to encourage more temporally proximal mood reporting. However, given the variance in the ability of individuals with SMI to promptly report data due to mood variations and social stigma issues [25], pragmatic visualization designs for this domain should provide the capability of representing both momentary and retrospective data reports.

4 CONCLUSION AND FUTURE WORK

The visualization presented in this work provides users a way to interact with and explore multi-source (self-tracked and co-tracked) mental health data. Visualization requirements were drawn from

a typology of sources of uncertainty, which are particularly important given the subjective nature of mental health data (in this example, perceived mood). The prototype interface was designed with considerations from prior empirical studies with clinicians and interpersonal studies in psychology, and is expected to improve empathic accuracy of mood state in partnerships, leading to improved relationship satisfaction and support for managing serious mental illnesses. In addition, the ability to compare consistency across two sources of the same mental health variable (for example, the mood of an individual managing BD) is expected to provide additional information for mental health professionals in a clinical context.

The developed prototype visualization (and sample data) currently resides in an Observable notebook, and is available to the public. Planned future work will implement the visualization into a mobile web app which facilitates both self-tracking and co-tracking alongside data visualizations. Given the novelty of a co-tracking system, it will be necessary to perform an *in situ* study to explore clinical usefulness as well the effects of co-tracking on empathic accuracy in partnerships. The qualitative and quantitative results of this study are expected to further inform the design of interfaces for supporting and visualizing multi-source data to support well-being in both informal and clinical contexts.

While the present work is focused on a case study of visualizing multi-source mood data for managing bipolar disorder, the typology of uncertainty and the mechanisms by which uncertainty enters mental health data streams can both help to inform the design of analytics systems that support well-being, more generally. The nature of mental health data and tendency for systems to impose certain representations of subjective affective experiences motivate the inclusion of uncertainty in mental health data visualizations.

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REFERENCES

[1] Ross J Baldessarini and Leonardo Tondo. 2003. Suicide risk and treatments for patients with bipolar disorder. *JAMA* 290, 11 (Sept. 2003), 1517–1519. https://doi.org/10.1001/jama.290.11.1517

[2] M. Bostock, V. Ogievetsky, and J. Heer. 2011. D³ Data-Driven Documents. *IEEE Transactions on Visualization and Computer Graphics* 17, 12 (Dec. 2011), 2301–2309. https://doi.org/10.1109/TVCG.2011.185

[3] Clara Caldeira, Yu Chen, Lesley Chan, Vivian Pham, Yunan Chen, and Kai Zheng. 2018. Mobile apps for mood tracking: An analysis of features and user reviews. *AMIA Annual Symposium Proceedings* 2017 (April 2018), 495–504. https://pubmed.ncbi.nlm.nih.gov/29854114/

[4] Karen Church, Eve Hoggan, and Nuria Oliver. 2010. A study of mobile mood awareness and communication through MobiMood. In *Proceedings of the 6th Nordic Conference on Human-Computer Interaction: Extending Boundaries (NordiCHI '10)*. ACM Press, New York, NY, 128–137. https://doi.org/10.1145/1868914.1868933

[5] Margaret S Clark, Katherine R Von Culin, Elizabeth Clark-Polner, and Edward P Lemay. 2017. Accuracy and projection in perceptions of partners' recent emotional experiences: Both minds matter. *Emotion* 17, 2 (March 2017), 196–207. https://doi.org/10.1037/emo0000173

[6] Ellen Frank. 2007. Interpersonal and social rhythm therapy: A means of improving depression and preventing relapse in bipolar disorder. *Journal of Clinical*

Psychology 63, 5 (2007), 463–473. https://doi.org/10.1002/jclp.20371

[7] Emma Gliddon, Steven J. Barnes, Greg Murray, and Erin E Michalak. 2017. Online and mobile technologies for self-management in bipolar disorder: A systematic review. *Psychiatric Rehabilitation Journal* 40, 3 (Sept. 2017), 309–319. https://doi.org/10.1037/prj0000270

[8] Gevorg Grigoryan and Penny Rheingans. 2004. Point-based probabilistic surfaces to show surface uncertainty. *IEEE Transactions on Visualization and Computer Graphics* 10, 5 (Sept. 2004), 564–573. https://doi.org/10.1109/TVCG.2004.30

[9] Michael J D Hoefer, Lucy Van Kleunen, Cassandra Goodby, Lanea B Blackburn, Priyanka Panati, and Stephen Voida. 2021. The multiplicative patient and the clinical workflow: Clinician perspectives on social interfaces for self-tracking and managing bipolar disorder. In *Proceedings of the ACM Conference on Designing Interactive Systems (DIS '21)*. ACM Press, New York, NY, 907–925. https://doi.org/10.1145/3461778.3461995

[10] Maryhope Howland. 2016. Reading minds and being invisible: The role of empathic accuracy in invisible support provision. *Social Psychological and Personality Science* 7, 2 (March 2016), 149–156. https://doi.org/10.1177/1948550615606195

[11] Dandan Huang, Melanie Tory, Bon Adriel Aseniero, Lyn Bartram, Scott Bateman, Sheelagh Carpendale, Anthony Tang, and Robert Woodbury. 2015. Personal visualization and personal visual analytics. *IEEE Transactions on Visualization and Computer Graphics* 21, 3 (March 2015), 420–433. https://doi.org/10.1109/TVCG.2014.2359887

[12] Jessica Hullman. 2020. Why authors don't visualize uncertainty. *IEEE Transactions on Visualization and Computer Graphics* 26, 1 (Jan. 2020), 130–139. https://doi.org/10.1109/TVCG.2019.2934287

[13] William Ickes and Sara D Hodges. 2013. Empathic accuracy in close relationships. In *The Oxford Handbook of Close Relationships*, Jeffry A Simpson and Lorne Campbell (Eds.). Oxford University Press, Oxford, UK, 348–373. https://doi.org/10.1093/oxfordhb/9780195398694.013.0016

[14] Thomas R Insel. 2008. Assessing the economic costs of serious mental illness. *American Journal of Psychiatry* 165, 6 (June 2008), 663–665. https://doi.org/10.1176/appi.ajp.2008.08030366

[15] Christina Kelley, Bongshin Lee, and Lauren Wilcox. 2017. Self-tracking for mental wellness: Understanding expert perspectives and student experiences. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM Press, New York, NY, 629–641. https://doi.org/10.1145/3025453.3025750

[16] Nam Wook Kim, Hyejin Im, Nathalie Henry Riche, Alicia Wang, Krzysztof Gajos, and Hanspeter Pfister. 2019. DataSelfie: Empowering people to design personalized visuals to represent their data. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM Press, New York, NY, Article 79, 12 pages. https://doi.org/10.1145/3290605.3300309

[17] Robert D Laing, Herbert Phillipson, and A Russell Lee. 1966. *Interpersonal Perception*. Tavistock Publications, London, UK.

[18] Ian Li, Anind Dey, and Jodi Forlizzi. 2010. A stage-based model of personal informatics systems. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '10)*. ACM Press, New York, NY, 557–566. https://doi.org/10.1145/1753326.1753409

[19] Suresh K Lodha, Alex Pang, Robert E Sheehan, and Craig M Wittenbrink. 1996. UFLOW: visualizing uncertainty in fluid flow. In *Proceedings of the 7th IEEE Visualization Conference (VIS '96)*. IEEE Computer Society Press, Los Alamitos, CA, 249–254. https://doi.org/10.1109/VISUAL.1996.568116

[20] Mark Matthews, Elizabeth Murnane, and Jaime Snyder. 2017. Quantifying the changeable self: The role of self-tracking in coming to terms with and managing bipolar disorder. *Human–Computer Interaction* 32, 5–6 (Nov. 2017), 413–446. https://doi.org/10.1080/07370024.2017.1294983

[21] Mark Matthews, Stephen Voida, Saeed Abdullah, Gavin Doherty, Tanzeem Choudhury, Sangha Im, and Geri Gay. 2015. In situ design for mental illness: Considering the pathology of bipolar disorder in mHealth design. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '15)*. ACM Press, New York, NY, 86–97. https://doi.org/10.1145/2785830.2785866

[22] Nina McCurdy, Julie Gerdes, and Miriah Meyer. 2019. A framework for externalizing implicit error using visualization. *IEEE Transactions on Visualization and Computer Graphics* 25, 1 (Jan. 2019), 925–935. https://doi.org/10.1109/TVCG.2018.2864913

[23] David J Miklowitz and Bowen Chung. 2016. Family-focused therapy for bipolar disorder: Reflections on 30 years of research. *Family Process* 55, 3 (Sept. 2016), 483–499. https://doi.org/10.1111/famp.12237

[24] Simone Mora, Verónica Rivera-Pelayo, and Lars Müller. 2011. Supporting mood awareness in collaborative settings. In *Proceedings of the 7th International Conference on Collaborative Computing: Networking, Applications and Worksharing (CollaborateCom '11)*. ICST, Ghent, Belgium, 268–277. https://doi.org/10.4108/icst.collaboratecom.2011.247091

[25] Elizabeth L Murnane, Tara G Walker, Beck Tench, Stephen Voida, and Jaime Snyder. 2018. Personal informatics in interpersonal contexts: Towards the design of technology that supports the social ecologies of long-term mental health management. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW

[26] Jeungmin Oh and Uichin Lee. 2015. Exploring UX issues in Quantified Self technologies. In *Proceedings of the 2015 Eighth International Conference on Mobile Computing and Ubiquitous Networking (ICMU)*. IEEE, Piscataway, NJ, 53–59. https://doi.org/10.1109/ICMU.2015.7061028

[27] Nickola C Overall and Margaret S Clark. 2020. Does expressing emotions enhance perceptual accuracy of negative emotions during relationship interactions? *Emotion* 20, 3 (April 2020), 353–367. https://doi.org/10.1037/emo0000653

[28] Lace Padilla, Matthew Kay, and Jessica Hullman. 2021. Uncertainty visualization. In *Wiley StatsRef: Statistics Reference Online*. John Wiley & Sons, Hoboken, NJ. https://doi.org/10.1002/9781118445112.stat08296

[29] Lace M K Padilla, Maia Powell, Matthew Kay, and Jessica Hullman. 2021. Uncertain about uncertainty: How qualitative expressions of forecaster confidence impact decision-making with uncertainty visualizations. *Frontiers in Psychology* 11, Article 579267 (Jan. 2021), 23 pages. https://doi.org/10.3389/fpsyg.2020.579267

[30] Alex T Pang, Craig M Wittenbrink, and Suresh K Lodha. 1997. Approaches to uncertainty visualization. *The Visual Computer* 13, 8 (Nov. 1997), 370–390. https://doi.org/10.1007/s003710050111

[31] Brian Parkinson, Rob B Briner, Shirley Reynolds, and Peter Totterdell. 1995. Time frames for mood: Relations between momentary and generalized ratings of affect. *Personality and Social Psychology Bulletin* 21, 4 (April 1995), 331–339. https://doi.org/10.1177/0146167295214003

[32] Justin Petelka, Lucy Van Kleunen, Liam Albright, Elizabeth Murnane, Stephen Voida, and Jaime Snyder. 2020. Being (in)visible: Privacy, transparency, and disclosure in the self-management of bipolar disorder. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. ACM Press, New York, NY, Article 446, 14 pages. https://doi.org/10.1145/3313831.3376573

[33] Matthew Price, Erica K Yuen, Elizabeth M Goetter, James D Herbert, Evan M Forman, Ron Acierno, and Kenneth J Ruggiero. 2014. mHealth: A mechanism to deliver more accessible, more effective mental health care. *Clinical Psychology & Psychotherapy* 21, 5 (Sept.–Oct. 2014), 427–436. https://doi.org/10.1002/cpp.1855

[34] Amon Rapp and Federica Cena. 2014. Self-monitoring and technology: Challenges and open issues in personal informatics. In *Universal Access in Human-Computer Interaction: Design for All and Accessibility Practice (UAHCI 2014)*. Springer International, Cham, Switzerland, 613–622. https://doi.org/10.1007/978-3-319-07509-9_58

[35] Haran Sened, Iftah Yovel, Eran Bar-Kalifa, Reuma Gadassi, and Eshkol Rafaeli. 2017. Now you have my attention: Empathic accuracy pathways in couples and the role of conflict. *Emotion* 17, 1 (Feb. 2017), 155–168. https://doi.org/10.1037/emo0000220

[36] Jaime Snyder, Elizabeth Murnane, Caitie Lustig, and Stephen Voida. 2019. Visually encoding the lived experience of bipolar disorder. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM Press, New York, NY, Article 133, 14 pages. https://doi.org/10.1145/3290605.3300363

[37] Poorna Talkad Sukumar, Gonzalo J Martinez, Ted Grover, Gloria Mark, Sidney D'Mello, Nitesh Chawla, Stephen M Mattingly, and Aaron D Striegel. 2020. Characterizing exploratory behaviors on a personal visualization interface using interaction logs. In *Proceedings of EUROVIS 2020—Short Papers*. The EuroGraphics Association, Geneva, Switzerland, 79–83. https://doi.org/10.2312/evs.20201052

[38] Judi Thomson, Elizabeth Hetzler, Alan MacEachren, Mark Gahegan, and Misha Pavel. 2005. A typology for visualizing uncertainty. In *Proceedings of Visualization and Data Analytics 2015 (SPIE 5669)*. SPIE, Bellingham, WA, 146. https://doi.org/10.1117/12.587254

[39] Sebastian Trautmann, Jürgen Rehm, and Hans-Ulrich Wittchen. 2016. The economic costs of mental disorders. *EMBO Reports* 17, 9 (Sept. 2016), 1245–1249. https://doi.org/10.15252/embr.201642951

[40] Craig M Wittenbrink, Alex T Pang, and Suresh K Lodha. 1996. Glyphs for visualizing uncertainty in vector fields. *IEEE Transactions on Visualization and Computer Graphics* 2, 3 (Sept. 1996), 266–279. https://doi.org/10.1109/2945.537309