Buildings in Harmony with the Occupants: Emotional Tracking and Dynamic Feedback to Enhance Well-being

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Dedication

In loving memory of my mother
To my lovely family,
For all your support

Executive Summary

Environmental Protection Agency (EPA) reports that Americans, on average, spend around 90% of their lives in indoor environments. While Indoor Environmental Quality (IEQ) significantly impacts the occupants' physical and mental well-being, buildings are not designed to collaborate with occupants, enhance their well-being, or communicate how occupants can reduce their environmental impact (i.e., energy consumption). We believe the recent advancements in affective computing, human-computer interaction, and behavioral theories derived from psychology and sociology can be incorporated to design and operate smart buildings that sense and react to occupants' emotional and behavioral changes. Within clinical psychology, passive sensing techniques have been utilized in combination with intervention strategies to improve patient states for depression and anxiety. While the benefits of digital tracking technologies are widely replicated regarding physical health and behavior, the effects of emotional tracking have not been studied longitudinally in the context of smart buildings. Any benefits from emotion tracking can be incorporated into a dynamic tracking and feedback system to improve its users' general well-being.

Our findings from the literature review reveal that multiple theories include emotions as a major construct affecting occupant behavior and comfort in buildings, which may influence how occupants interact with building systems, impacting buildings' total energy consumption. However, research on longitudinal sensing of occupant emotions and behavior has been far limited to link the emotions and behavior to the different constructs identified in behavioral science theories. Longitudinal emotion and behavior sensing in smart buildings create an opportunity to react to user-specific needs and emotions and increase occupants' emotional awareness by providing feedback on their emotional states' trends.

To address these gaps, in this thesis (1) a literature review is conducted to identify how behavioral theories can explain the role of emotional states and occupant behavior in interactions with building systems. Based on the identified gaps in the literature (2) a sensing framework is introduced to longitudinally sense occupants' emotional states subjectively, through daily surveys, and objectively through cameras deployed in the Living Link Lab testbed. Lastly, (3) a set of longitudinal studies are conducted to evaluate the impacts of emotional tracking and feedback on individuals.

Through the longitudinal studies, several hypotheses related to the potential effects of digital emotions tracking on individuals' emotional trends were evaluated. The results of the statistical analyses indicate that tracking daily emotions increases the stickiness of positive emotions. We hypothesize that this effect is due to the difference in recall of positive and negative emotions. Research suggests that memories associated with negative emotions are easier to recall than memories related to negative emotions. This gap in memory recall means tracking of emotions can improve recall of positive emotions. Thinking about and remembering positive experiences, in turn, has shown to benefit an individual's mental health significantly. The finding that tracking emotions can improve recall and stickiness of positive emotions has implications for dynamic feedback and intervention mechanisms to enhance well-being.

We incorporate a sensing framework to longitudinally sense occupants' emotional states subjectively, through daily surveys, and objectively through cameras deployed in the Living Link Lab testbed. This platform also incorporates an online dashboard with visualized data and controls for smart devices in buildings. The dashboard will use subjective reports and video data to provide digital tracking and feedback on user behavior and emotions. Furthermore, longitudinal data on emotions and objective measurements of the sensors and cameras can link the identified constructs in behavioral theories to occupants' behavior and emotions. Finally, the subjective and objective measurements can be combined to verify the external and internal validity of the impact of emotions tracking and intervention strategies on occupant emotion and behavior.

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1. Introduction and Background

Section 1.1 includes a summary of the motivations for emotion detection in smart buildings and their potential applications to improve building performance, occupant comfort, and productivity. Our initial review of the literature (summarized in section 1.2) revealed that various emotion regulation techniques and intervention strategies greatly benefit individuals suffering from mental health issues such as anxiety, stress, and depression. Section 1.3 discusses the prevalence of digital tracking and intervention techniques and their benefits towards achieving goals and productivity. Section 1.4 discusses the research objectives of this research.

1.1. Human Emotions and Building Performance

Changes in indoor environmental quality (IEQ) have significant effects on occupants' emotional and physical well-being (US EPA, 2017). The emotional and physical well-being of occupants, in turn, affects their behavior, performance, and comfort levels (Heydarian et al., 2020; Wang & Liu, 2020). Although Americans, on average, spend around 90 percent of their time indoors (US EPA, 2017), buildings are not designed to collaborate with occupants, enhance their well-being, or communicate how occupants can reduce their environmental impact. Furthermore, occupant behavior and their subjective perception of comfort directly influence the energy consumption in buildings. For instance, people feel warmer when feeling bored (Alaoui-Ismaïli et al., 1997), and therefore, might turn on the AC or open the windows to cool themselves. Smart buildings can potentially react to user emotions' changes and automatically adjust the environment to increase their comfort.

According to International Energy Agency (IEA) reports, buildings and their energy management systems make up one-third of energy consumption worldwide and 40% of the United States' energy consumption (Energy Information Administration, 2020; International Energy Agency, 2020). Occupants’ behavior and interaction with buildings significantly influence building energy consumption (Hong et al., 2016; Janda, 2011). Consequently, several approaches have been introduced to model and quantify the dynamics of occupants’ behavior within indoor environments and the impact of interventions on building energy consumption (Abrahamse et al., 2007; Carrico & Riemer, 2011; Dixon et al., 2015; Tanner & Henze, 2013).

Our literature review on how behavioral theories can explain occupant behavior (Heydarian et al., 2020) revealed that several behavioral theories include personal constructs such as attitudes, emotion, anticipated emotions, and intentions as a significant influence on behavior and environmental comfort. For instance, in the Theory of Goal-Directed Behavior, positive and negative anticipated emotions regulate the desire to act in individuals (Ajzen & Madden, 1986; Bagozzi et al., 2000), and in the Theory of Interpersonal Behavior (TIB), affect regulates the intention to action (Triandis, 1979) - Figure 1. Furthermore, the theory of Self-regulated Behavior Change includes negative emotions as a driver for self-regulation and behavior changes. Several studies have demonstrated the effects of emotions on occupants' interactions with buildings. For instance, research by Lee et al. indicates that energy-saving intentions increase energy-saving behavior and satisfaction with environmental comfort (T. K. Lee et al., 2012). Furthermore, Webb et al. found that positive anticipated emotions were significant predictors of intentions, while negative anticipated emotions did not significantly influence intentions (Webb et al., 2013). In addition, Carrico & Riemer and Abrahamse et al. found that feedback combined with strategies such as peer education (Abrahamse et al., 2007) and goal setting (Carrico & Riemer, 2011) could reduce energy consumption in buildings by four to seven percent.

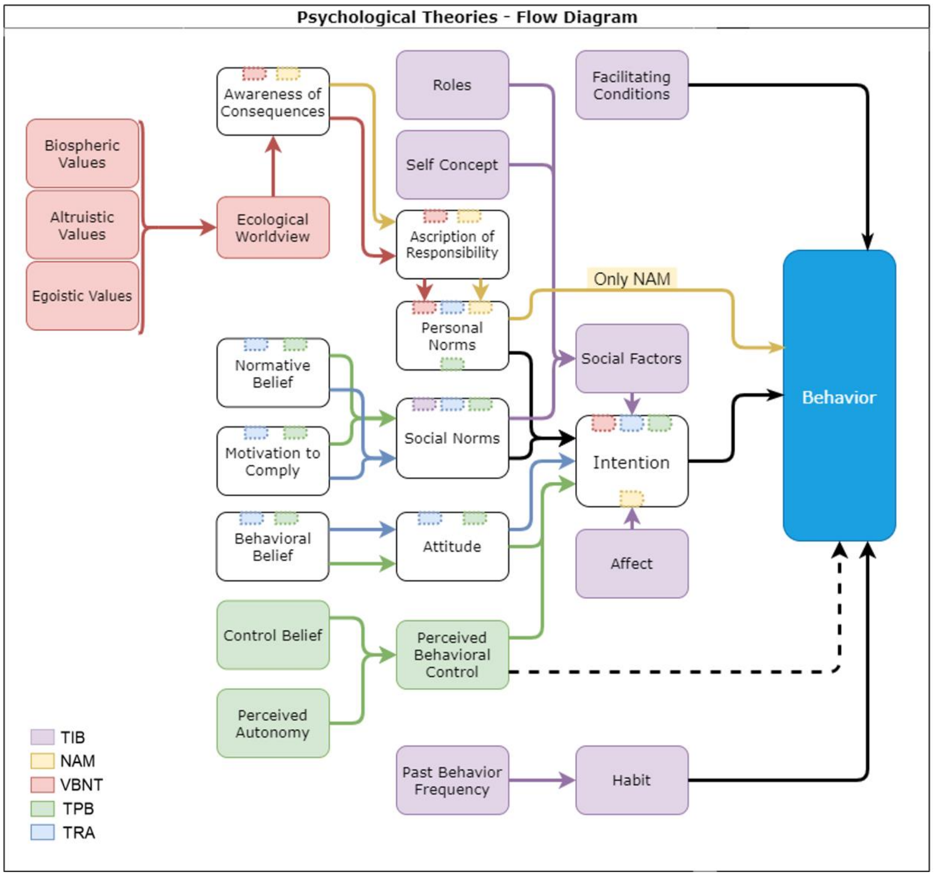

Figure 1 - "Overview of the five most commonly applied psychological theories along with their constructs." (Heydarian et al., 2020)

This interaction between occupants' emotions and their behavior presents an opportunity for emotion-tracking technologies in smart buildings to improve the subjective well-being of occupants and reduce energy consumption. To achieve this, we should design smart building systems focusing on factors affecting occupant behavior and well-being. Thus, it is necessary to understand how the interactions between a human-in-the-loop building and occupants affect energy consumption, operation costs, occupant satisfaction, and well-being. A step towards understanding users' emotional interaction with smart buildings is to investigate the possible sensing and intervention strategies to track and improve the user's emotional state. Furthermore, we should explore the impact of emotion-sensing and tracking should

1.2. Interventions on Mental Health and Emotional Well-being

Our emotions vary daily, and while we can deploy strategies to improve our well-being (e.g., coping mechanisms; Cheng et al., 2014), they are often affected by uncontrollable external situations. The existing research in psychology shows that various intervention strategies such as expressive writings effectively enhance individuals' emotional well-being. Prior research has explored the impact of reflecting on or reporting emotions on subjective well-being. Expressive writing provides individuals an opportunity to self-reflect and cope with stressors such as medical conditions and work stress. Research suggests that keeping diaries and writing about emotions (Lieberman et al., 2007) and talking with others (venting) (Pennebaker & Beall, 1986) help individuals cope and regulate their emotions. In a series of studies, Burton and King observed that even a two-minute daily emotional expression through writing leads to lower physical health complaints (Burton & King, 2008). Talking to friends and families has also exhibited benefits towards coping and regulating stress in academic and professional environments (Pierceall & Keim, 2007). Furthermore, cognitive-behavioral therapy (CBT) interventions which focus on awareness of emotions and addressing cognitive distortions, has been found as effective as psychoactive medications in some cases, such as in treating minor depression, anxiety, and post-traumatic stress disorder (PTSD) (Otto et al., 2010; Watts et al., 2015; Roshanaei-Moghaddam et al., 2011).

1.3. Prevalence of Digital Behavior Tracking and Interventions

Recent advances in technology (e.g., mobile devices and wearables) allow for platforms that track a wide range of daily behaviors, habits, and physical health. This ranges from exercise levels, and calorie counts to sleep quality and work productivity (Boukhechba et al., 2018; Boukhechba & Barnes, 2020; Payne et al., 2015; Shin et al., 2017; Zahry et al., 2016). Research has shown the benefits of tracking such behaviors, including achieving personal goals (Herrmanny et al., 2016) and personal fitness (Dennison et al., 2013; Higgins, 2016; S.-H. Lee et al., 2019), especially when paired with different incentives and reward mechanisms (Joseph et al., 2014; Spittaels et al., 2007).

Dennison et al. show that when consumers track their fitness and are not satisfied with their performance, the tracking device could be a reminder for them to exercise more (Dennison et al., 2013). Similarly, for calorie count tracking applications, consumers may choose to consume healthier options (Dunn et al., 2019). To improve work productivity, Borghouts et al. demonstrated that digital tracking and feedback mechanisms help users identify unproductive events (e.g., interruptions) and help them focus on their primary tasks (Borghouts et al., 2020).

Thus, a large stream of research has demonstrated the potential benefits of tracking physical health or work behaviors (e.g., step counts, counting calories, sleep). We build on this research by examining the benefits or consequences of tracking mental health rather than physical health. In particular, we aim to examine the impact of tracking emotions on people's emotional well-being. When consumers track physical behaviors, they often report their behavior, such as their daily calories, and can view their past behavior over the past week or month. Thus, we operationalize tracking emotions as participants reporting their emotions daily with the ability to view their past emotions over the previous week or month. Participants thus reflect on their current daily emotions while tracking emotion reminds them of their past emotions.

Although there has been significant growth in the number of studies that evaluate the impact of digital behavior-tracking technologies on consumer behavioral changes, most of these studies focus on physical activities or behaviors that can be objectively measured. However, it is not clear whether providing tracking for non-physical and subjective behavior (e.g., emotions) can help consumers make conscious decisions to boost their emotional state and subjective well-being through self-regulation and motivation.

As smart wearable technologies become more popular and accurate, it opens up opportunities to detect and track emotional and mental states using signal processing and machine learning techniques (Boukhechba et al., 2018; Boukhechba & Barnes, 2020). For example, Domínguez-Jiménez et al. investigated the effect of visual and physiological data collected via cameras and wearable sensors to evaluate emotions (Domínguez-Jiménez et al., 2020), which is helpful for mental health interventions such as CBT. Consequently, recently mood tracking applications have become more popular with the hope to address mental health issues such as depression and bipolar disorders (Bakker et al., 2018; Branco et al., 2021). While there is some evidence for their effectiveness in managing anxiety and depression symptoms (Buttazzoni et al., 2021; McCloud et al., 2020), there is still no clear design guideline to ensure their positive impacts.

1.4. Research Objectives

1.4.1. Impact of Digital Emotion Tracking and Emotional Awareness

In this research, we are interested in evaluating the impact of longitudinal emotion tracking, where participants report and keep track of their subjective emotional states. Specifically, we will investigate whether providing visual tracking of emotion trends to individuals may affect their emotions. Furthermore, we aim to evaluate whether tracking subjective measures (i.e., mental health) has similar positive impacts as objective measures (e.g., physical health). Any difference in the effects of tracking, writing, and feedback on individuals' emotions will have implications for dynamic intervention systems based on tracking, expressing, and providing feedback. This report will present our findings in longitudinal studies performed on online emotion tracking and electronic diaries.

1.4.2. Hypothesis

After reviewing the literature, we came up with the following hypothesis for the possible effects of tracking vs. reporting emotions.

Strength of Positive vs. Negative Information

Research suggests that recalling positive memories and happy life experiences buffer acute stress response and reduce the risk of depression in adolescents (Askelund et al., 2019; Speer & Delgado, 2017). Kensinger showed that events associated with negative emotions are easier to recall than events associated with positive emotions (Kensinger, 2007). The difference in recall of memories means that feedback on information about positive and negative events, the new information recalled for positive events will potentially be greater than the new information gained about negative events. The difference in memory recall by tracking vs. reporting, or the ‘information gain,’ can impact emotions. Furthermore, higher stickiness of negative memory recall means that even if tracking visualizations provide similar amounts of information for positive and negative events, the net ‘information gain’ for positive events will be more than the information gain for negative events. Therefore, we hypothesize that a digital emotional tracking platform may benefit the mental health of the participants by facilitating the recall of recent positive emotions and the events associated with these emotions. (H1)

H1: Digital emotional tracking may benefit the participants' mental health by facilitating the recall of recent positive emotions and the events associated with these emotions.

1.4.3. Behavior and Emotion Research in Living Link Lab

Behavioral studies require multilevel analysis of objective measurements and subjective reports to ensure the external validity and applicability of their findings. Upon our preliminary studies revealing positive effects for digital emotion tracking, we plan to incorporate emotion and behavioral sensing architecture in the Living Link Lab to analyze the longitudinal effects of feedback and affective tracking on occupants. Our proposed architecture will extend the Living Link Lab platform with interactive surveys and video collection to sense and track participating occupants' emotions and behavior. Living Link Lab is a behavioral and environmental testbed at the systems engineering department at UVA. The existing array of sensors and infrastructure enables accurate tracking of environmental factors and specific behavior such as interactions with doors and windows. Living Link Lab already utilizes environmental sensors such as light level, air quality, occupancy, status of doors and windows, air temperature, and power usage sensors.

An integrated self-reporting and sensing platform will allow comparing sensors' objective measurements against ground truths and subjective reports of the participants. This enables further analysis of behavioral theories that rely on constructs such as attitude, which cannot be directly measured through sensors. The comparison of the subjective and objective measures allows validation and calibration of the sensors and analysis algorithms. Combining an interactive survey platform such as Qualtrics (Qualtrics, 2005) with our existing sensor infrastructure and user interfaces will be invaluable for integrated research on occupant behavior, environmental monitoring and management, and health and well-being research.

2. Longitudinal Emotion Tracking

We will use Qualtrics to generate tailored surveys for each user and MTurk to recruit participants and distribute the surveys to the participants. The potential participants will be informed about the study's payments, duration, and terms during an initial survey. The participants who agree to the terms of the study will be randomly assigned to the different treatment/control groups for daily surveys and completed several questionnaires, including and Satisfaction With Life (SWL) (Diener et al., 1985), Big Five Inventory (BFI) (John & Srivastava, 1999), Positive and Negative Affect Schedule (PANAS) (Watson et al., 1988), Cantril Self-Anchoring Striving Scale (Cantril, 1965), and Brief Self-Control Scale (Tangney et al., 2004). Over the next few days, the participants will receive daily surveys tailored to their treatment/control group. On the last day of the study, the participants will receive a survey that, similar to the initial survey, includes questions about subjective well-being measures. The final survey will also ask the participants to report their overall opinion and experience with the study.

We will also collect personality measures, self-control measures, how much time people spend on different tasks such as using phones, exercising, outside, listening to music, socializing with others, and sleeping. We will also ask about the demographics of the participants, such as employment status, education, income, marital status, gender, age, and ethnicity. The details of the two longitudinal studies are provided in the following sections.

2.1. Overview of the Tracking Process

We utilize Python, Qualtrics API, and the Matplotlib library to generate visual reminders for participants' emotional trends. We upload the visualizations to a Data Storage bucket on Google Cloud with unique access links for each participant. The Qualtrics surveys utilize these unique links to retrieve and show the tracking visualizations to the participants in the tracking group. The overview of the tracking visualization process is available in Figure 2.

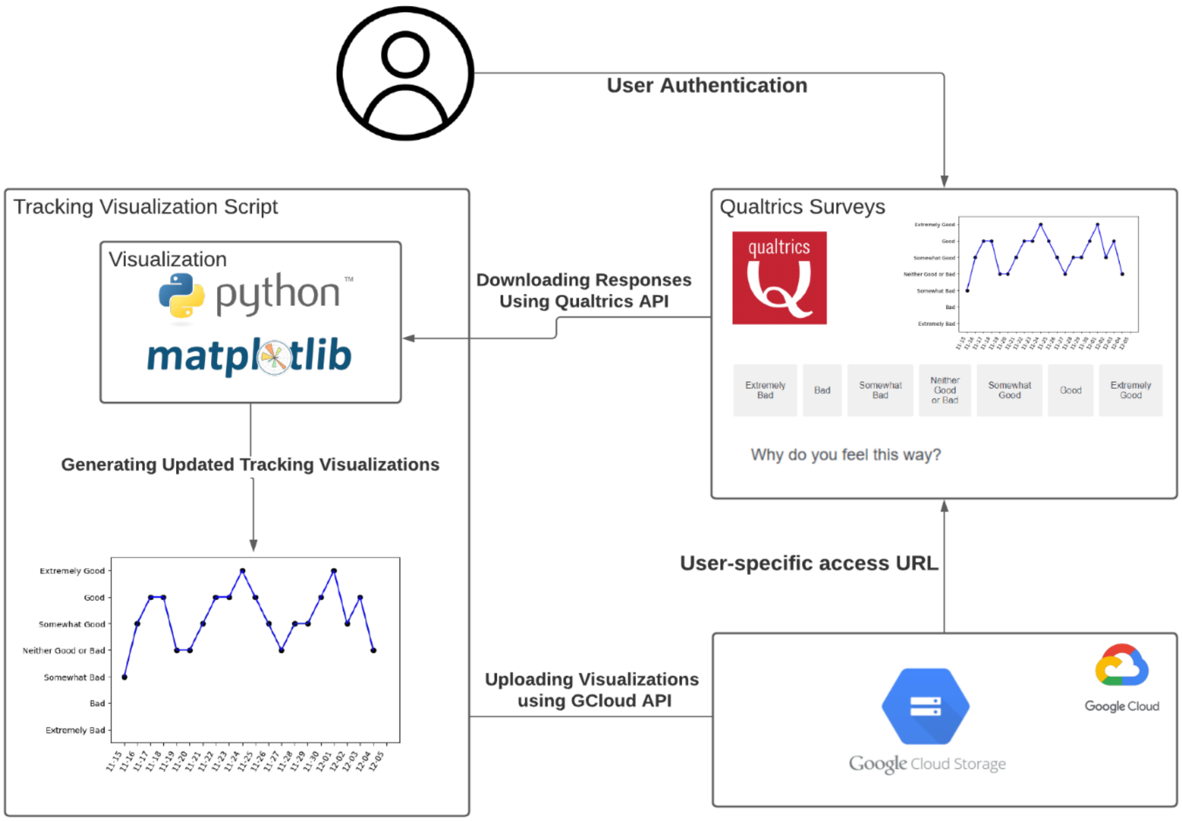

Figure 2 - Overview of the Tracking System

2.2. Study 1: Influence of Emotion Type and Emotion Reminder on Emotion Stickiness

2.2.1. Motivation

Study 1 explores whether emotions vary in their stickiness over time, that is, whether positive Emotion or negative Emotion is more likely to persist for the next day. Further, study 1 tests whether reminding participants about their emotional state history is linked to emotion stickiness. In other words, study 1 explores our central question in a 28-day longitudinal study: does tracking (vs. reporting) affect emotion stickiness, depending on emotion type (i.e., positive vs. negative).

2.2.2. Experiment Design

We will use MTurk and an initial survey to recruit 600 participants for a 30 day-study (Figure 3). Participants who complete the initial survey will receive $0.60 payments. The potential participants will be informed about the study's payments, duration, and terms during the initial survey. The participants who agree to the study's terms will be randomly assigned to the different treatment/control groups for daily surveys. We will also collect a variety of subjective well-being and personality measures. Furthermore, the survey will include questions regarding the participants' demographics, such as employment status, occupation, education, income, marital status, gender, age, and ethnicity. The complete list of survey questions is available in Appendix A.

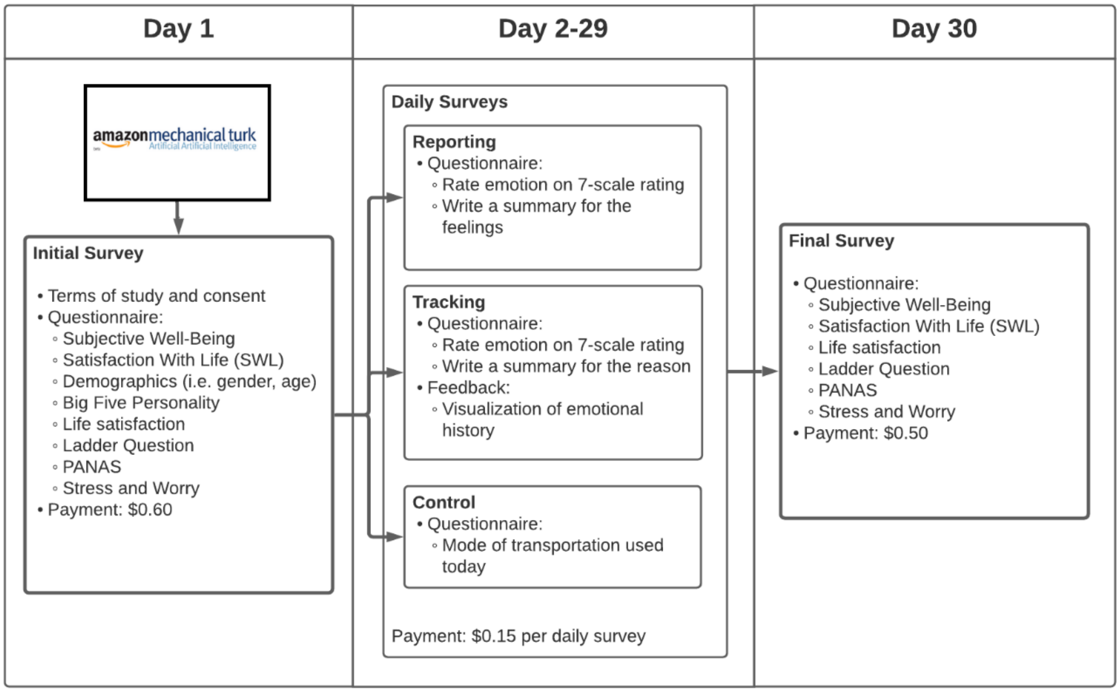

Figure 3 - The three stages of study 1: 1- Recruiting participants with MTurk and completing the initial survey. 2- Daily surveys sent to participants for 28 days. 3- Final survey sent on day 30.

The first study will include three groups of participants: 1-Control 2-Reporting 3-Tracking. From day 2 to day 29 of the study, the participants receive daily surveys tailored to their groups. The participants will receive $0.15 for every daily survey that they complete. The control group will only receive daily questions regarding the modes of transportation they used during the day. The treatment groups of *Reporting* and *Tracking* will report how they felt during the day on a 7-scale measure (ranging from 1 for ‘Extremely Bad’ to 7 for ‘Extremely Good’) and briefly write down the reason behind their emotions. The Tracking group will also see a graph visualization of the emotions that they had reported during the previous days of the study.

During the study, we will send daily surveys and reminders to the participants. Each survey will be available from 5 pm EST to 3 am EST the next day, except for Thanksgiving Day. During Thanksgiving, the surveys will be available from 4 pm EST to 4 am EST the next day. On day 30, the participants receive a survey that includes subjective well-being measures similar to the initial survey and asks the participants about their experience with the study. The final survey will be active from 12 pm for 24 hours and rewarded $0.50 for completing the survey. A summary of the survey setup is provided in Table 1.

Table 1 - Summary of the first longitudinal experiment

Study	Study 1
Beginning Date	Nov 15, 2018
Final Date	Dec 13, 2018
Duration	30 Days
Hours of Day (EST)	5:00 pm to 3:00 am the next day 4:00 pm to 4:00 am during Thanksgiving
Payments	\$0.60 initial survey \$0.15 per daily survey \$0.50 final survey
Bonus Payments	\$2 if they participated for at least 25 days
Number of Participants	600 (413 agreed to complete daily surveys)
Response Rate	275/413 completed at least 75% of daily surveys (21 days)
Demographics	202 females Mean age = 37
Groups	Control Reporting Tracking

2.2.3. Method

413 participants were recruited on Amazon Mechanical Turk (202 females, M_{age} = 37.01, $Range_{age}$ = [20, 77]). Before being assigned to condition, participants were asked to fill out a survey on key demographic attributes, including gender, age, education, income bracket, marital status, ethnicity, and employment status. The participants were also asked to fill out personality scales on extraversion, agreeableness, conscientiousness, stability, openness (John & Srivastava, 1999), and self-control (Tangney et al., 2004).

Next, participants were randomly assigned to one of the three conditions: *tracking*, *reporting*, and *control*. Participants in the control condition did not report any emotions and were only asked to report their transportation type ("What type of transportation did you use today?").

Participants in the tracking and reporting condition were asked to report their emotions for four consecutive weeks. Each day they would rate how they feel on a scale of 1 (extremely bad) to 7 (extremely good) and briefly describe in a text box why they feel that specific emotion ("Every day you will be asked to indicate (1) how you are feeling that day and (2) why you are feeling this way.").

Participants in the *tracking* group saw their reported past emotions over the last fourteen days in the form of a graph (see Figure 4). In the *reporting* group, they did not see their reported past emotions. At the end of the 28-day study, participants were asked about their overall emotional well-being.

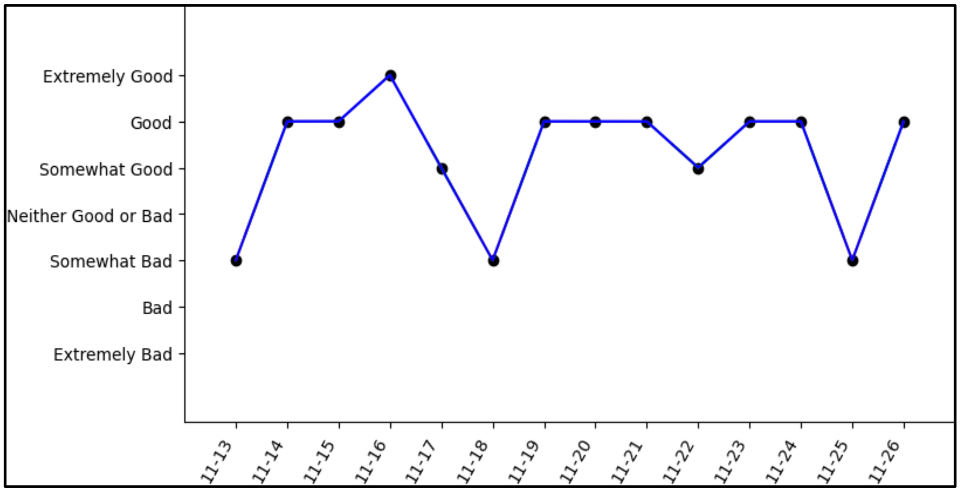

Figure 4 - Visualization example for the tracking group

2.2.4. Results

We first examined if participants differed in their overall emotional well-being that they reported at the end of the study, controlling for what they reported at the beginning of the study. We did not find that the tracking or feedback condition differed from the control condition.

Next, we examined our main hypothesis. We are interested in measuring how emotion stickiness is linked to emotion type (i.e., positive or negative) and emotion reminder (i.e., presence or absence of visualization reminder). We classify emotion type as positive when participants report their emotion as 5 (somewhat good), 6 (good), or 7 (extremely good). Emotion type is negative when participants rate their emotion as 1 (extremely bad), 2 (bad), or 3 (somewhat bad). Thus, when emotion is reported as 4 (neither good nor bad), it is considered neutral and is not included in our analyses. Emotion stickiness is coded as 1 if today's emotion is the same as tomorrow's (both are positive or both are negative) and coded as 0 if they are different (e.g., today is positive and tomorrow is negative or neutral).

Because only participants in the tracking and reporting condition report emotions, we only include these conditions in this analysis. Using a mixed-effect logistic regression, we predict emotion stickiness (0 or 1) from a dummy variable representing emotion type (positive or negative), a dummy variable representing the tracking vs. reporting condition (presence or absence), and a variable representing their interaction. Given that emotion stickiness may vary across individuals, we add a random effect for participant IDs.

As predicted, we find a significant interaction between emotion type and emotion reminder (B= -0.855, SE = 0.176, 95% CI = [-1.203, -0.512], $p < 0.001$, β= -0.170). While positive emotions were stickier than negative emotions in both conditions, positive emotions were relatively stickier if participants were in the tracking (vs. reporting) group (tracking: $M_{positive}$ = 1.753, $SD_{positive}$ = 0.431, $M_{negative}$ = 1.222, $SD_{negative}$ = 0.416, β = 2.370, SE = 0.141, 95% CI = [2.098, 2.652], $p <$ 0.001; reporting: $M_{positive}$ = 1.689, $SD_{positive}$ = 0.463, $M_{negative}$ = 1.328, $SD_{negative}$ = 0.470, β = 1.515, SE = 0.106, 95% CI = [1.309, 1.723], $p < 0.001$). Consequently, the interaction effect shows that the stickiness of positive emotions is amplified in the presence of emotion reminders (i.e., tracking group).

We also control for various factors, including gender, age, education, income bracket, marital status, ethnicity, employment status, and personality measures. We also control for the reason why participants feel negative or positive. To do so, we apply deep learning to classify participants' text into six different categories: health (short term or long term), work (including finances and goals), sleep, fun (including vacation, relationship, or any fun activity), future (including thinking about future and being spiritual), and none (no specific reason reported; see Supplementary Materials for details).

Robustness

The results for the effect of positive emotion hold when controlling for gender, age, race, employment status, marital status, education, natural log-transformed respondent income, reason category, self-control measure, and five main personality measures (B= 1.836, SE = 0.105, 95% CI = [1.631, 2.041], $p < 0.001$, β= 0.749). The interaction effect also holds consistent (B= -0.515, SE = 0.199, 95% CI = [-0.905, -0.126], $p < 0.01$, β= -0.116), however, the effect for group condition goes away (B = -0.160, SE = 0.124, 95% CI = [-0.402, 0.083], $p = 0.197$, β= -0.084).

Table 2 - Regression Results of Study 1: influence of emotion type and emotion reminder on emotion stickiness

Variables	(1)	(2)	(3)	(4)
Positive Emotion	1.848*** (0.084)	2.370*** (0.141)	1.836*** (0.105)	2.141*** (0.16)
Reporting Condition	-0.160* (0.067)	0.534*** (0.160)	-0.16 (0.124)	0.264 (0.205)
Positive emotion * Reporting Condition		-0.855*** (0.176)		-0.515** (0.199)
Male			0.028 (0.136)	0.041 (0.134)
White			0.202 (0.148)	0.192 (0.147)
Employed			0.148 (0.147)	0.136 (0.146)

Married			-0.128 (0.132)	-0.126 (0.131)
4-Year College			0.009 (0.124)	0.01 (0.122)
Age			0.006 (0.006)	0.007 (0.006)
Natural Log Transformed Earnings			-0.025 (0.026)	-0.025 (0.026)
Self-Control			0.107 (0.128)	0.108 (0.126)
Extraversion			0.006 (0.038)	0.005 (0.038)
Agreeableness			0.088 (0.054)	0.085 (0.053)
Conscientiousness			0.071 (0.077)	0.066 (0.076)
Stability			0.031 (0.049)	0.032 (0.048)
Openness			0.05 (0.05)	0.05 (0.05)
Reason Category			Yes	Yes
Participants			Yes	Yes
Constant	-0.817*** (0.085)	-1.253*** (0.130)	-2.654*** (0.537)	-2.844*** (0.555)
R2	0.162	0.169	0.2254	0.2248

Notes: (1) The coefficients reported above are the unstandardized coefficients. (2) All numerical predictor variables are mean-centered.

^ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.2.5. Discussion

Study 1 shows that positive emotions are stickier than negative emotions. If participants feel positive today, it is more likely that they will feel positive tomorrow. Further, the effect of positive emotion stickiness is present regardless of the assigned condition to the participants (absence or presence of remotion reminder).

Further, interaction analysis revealed that emotion reminders (i.e., tracking group) amplify positive emotion stickiness. If participants see a reminder of their past emotions and feel positive today, they are more likely to feel positive tomorrow. This result supports our hypothesis that emotional tracking benefits the participants' mental health by facilitating positive emotion recall (H1).

2.3. Study 2: Effect of Annotated Reminder on Emotion Stickiness

2.3.1. Motivation

Study 2 examines if we can replicate the effect of positive emotion stickiness from tracking (vs. feedback). Further, it examines whether providing participants' emotion history paired with annotation (i.e., the reported text) is linked to emotion stickiness. By reminding participants how they felt in the past and why they felt that way, the effect of tracking (vs. reporting) might differ. In particular, they may not clearly remember the reasons for their past emotions. Therefore, if people are reminded of the events and reasons for their past emotions, they, more consciously, manage their feelings.

2.3.2. Experiment Design

We will use MTurk and an initial survey to recruit 700 participants for a 22 day-study (Figure 5). Participants who complete the initial survey will receive $0.60 payments. The potential participants will be informed about the study's payments, duration, and terms during an initial survey. The participants who agree to the study's terms will be randomly assigned to the different treatment/control groups for daily surveys. We will also collect a variety of subjective well-being and personality measures. Furthermore, the survey will include questions regarding the participants' demographics, such as employment status, occupation, education, income, marital status, gender, age, and ethnicity. The complete list of survey questions is available in Appendix A.

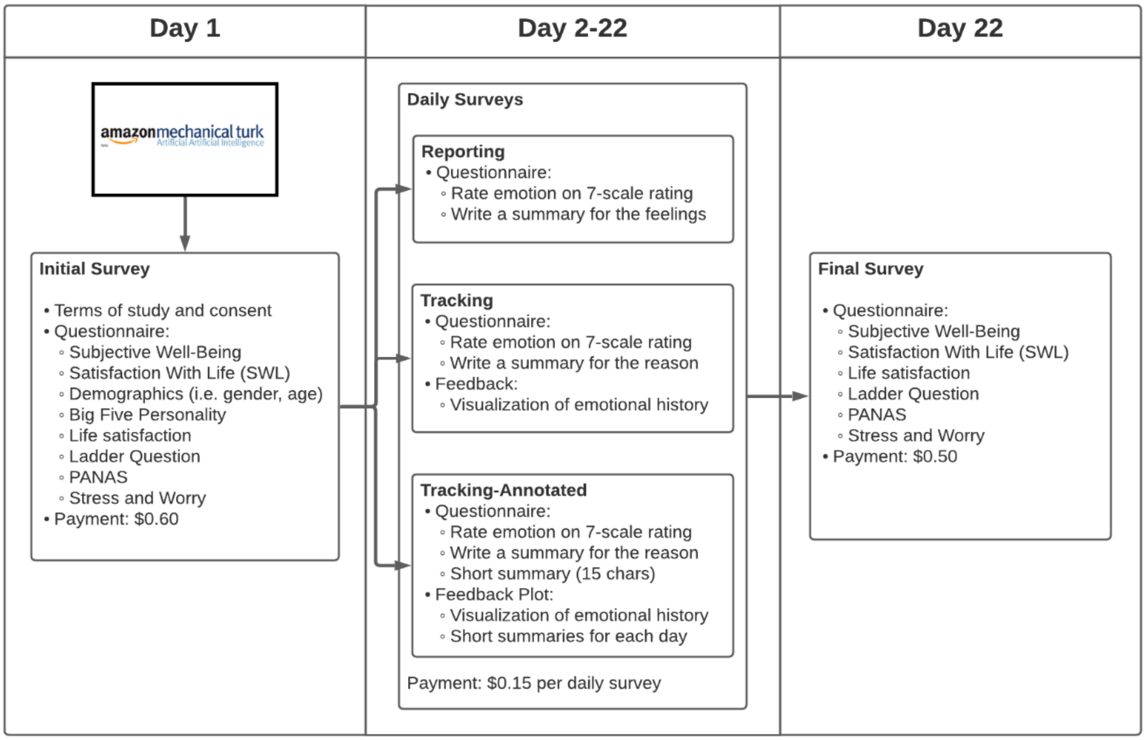

Figure 5 - The three stages of study 2: 1-Recruiting participants with MTurk and completing the initial survey. 2-Daily surveys sent to participants for 21 days. 3- Final survey sent on day 22.

The second study includes three groups: 1- *Reporting* 2-*Tracking* 3-*Tracking-Annotated*. From day 2 to day 22 of the study, the participants will receive daily surveys tailored to their groups. The participants will receive $0.15 for every daily survey that they complete. The *Reporting* and *Tracking* groups conditions will be identical to the conditions in study 1. The *Tracking-Annotated* group will be similar to the *Tracking* group, but the participants will also report a very brief explanation for their reported emotions (less than 15 characters). These short descriptions will be then included in the graphs of their previous emotions to provide context for the plots.

On day 22, the participants will receive the final survey, which includes subjective well-being measures similar to the initial study, and asks about their experience with the study. The final survey will be active from 12 pm for 24 hours and reward $0.50 for completing the survey. A summary of the survey setup is provided in Table 3.

Table 3 - Summary of the second longitudinal experiment

Study	Study 2
Beginning Date	Nov 6, 2019
Final Date	Nov 27, 2019
Duration	22 Days
Hours of Day (EST)	4:00 pm to 4:00 am
Payments	\$0.50 initial survey \$0.15 per daily survey \$0.50 final survey
Bonus Payments	\$2 if they participated for at least 18 days
Number of Participants	700 (612 agreed to complete daily surveys)
Response Rate	439/612 completed at least 75% of daily surveys (15 days)
Demographics	309 females Mean age = 37
Groups	Reporting Tracking Tracking - Annotated Graphs
Completion Rate	(439/612) completed 75% of daily surveys

2.3.3. Method

612 participants were recruited on Amazon Mechanical Turk (309 females, M_{age} = 37, $Range_{age}$ = [18, 80]). Like previous studies, participants were asked to fill out a survey on key demographic attributes, including gender, age, education, income bracket, marital status, ethnicity, and employment status. The participants were also asked to fill out personality scales on

extraversion, agreeableness, conscientiousness, stability, openness (John & Srivastava, 1999), and self-control (Tangney et al., 2004).

Next, participants were randomly assigned to one of the three conditions: *tracking*, *reporting*, and *tracking-annotate*. We asked the participants to report their emotions for three consecutive weeks (= 21 days). Each day they would rate how they feel on a scale of 1 (extremely bad) to 7 (extremely good) and briefly describe in a text box why they are feeling that specific emotion ("Every day you will be asked to indicate (1) how you are feeling that day and (2) why you are feeling this way."). Additionally, the participants in the *tracking-annotate* condition would see a visualization of their reported emotions in the past week and why they felt that way ("You will also see a graph that shows you the emotions you have experienced over the past week.") (see Figure 6). In the *tracking* group, participants only saw a visualization of emotions with no annotation, and in the *reporting* group, they did not see any visualization reminders.

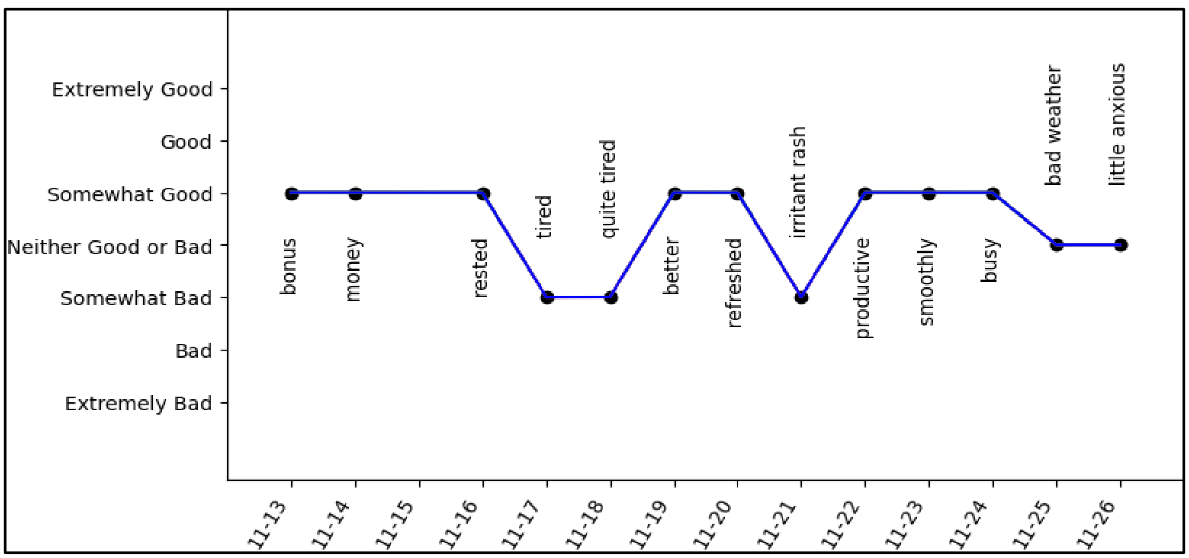

Figure 6 - Visualization example for the tracking-annotate group

2.3.4. Results

The results show that positive emotions are more likely to persist compared to negative emotions (N = 7616, $M_{positive}$ = 1.718, $SD_{positive}$ = 0.450, $M_{negative}$ = 1.314, $SD_{negative}$ = 0.464, B = 1.716, SE = 0.061, 95% CI = [1.597, 1.836], $p < 0.001$, β = 0.700). Results also show that providing visualization of emotion history for participants paired with annotation (i.e., tracking-annotate group) decreases the likelihood of the current emotion to persists for the next day ($M_{tracking}$ = 1.651,

$SD_{tracking}$ = 0.477, $M_{tracking\ annotate}$ = 1.625, $SD_{tracking\ annotate}$ = 0.484, $M_{reporting}$ = 1.623, $SD_{reporting}$ = 0.485, $B_{tracking\ annotate}$ = -0.128, SE = 0.063, 95% CI = [-0.251, -0.004], $p < 0.05$, β= -0.059, $B_{reporting}$ = -0.091, SE = 0.061, 95% CI = [-0.211, 0.03], p = 0.139, β= -0.043).

Further, supporting Study 1 results, there is a significant interaction between emotion type and emotion reminder (B = -0.324, SE = 0.146, 95% CI = [-0.611, -0.038], $p < 0.05$, β= -0.056). While positive emotions were stickier than negative emotions in all three conditions, positive emotion was relatively less sticky if participants were in the reporting (vs. tracking or tracking-annotate) condition, that is, when participants do not see any visualization reminder of their past emotions (tracking: $M_{positive}$ = 1.739, $SD_{positive}$ = 0.439, $M_{negative}$ = 1.305, $SD_{negative}$ = 0.461, β = 1.866, SE = 0.109, 95% CI = [1.655, 2.080], $p < 0.001$; tracking-annotate: $M_{positive}$ = 1.709, $SD_{positive}$ = 0.454, $M_{negative}$ = 1.292, $SD_{negative}$ = 0.455, β = 1.779, SE = 0.112, 95% CI = [1.561, 2.000], $p < 0.001$; reporting: $M_{positive}$ = 1.706, $SD_{positive}$ = 0.456, $M_{negative}$ = 1.339, $SD_{negative}$ = 0.474, β= 1.541, SE = 0.098, 95% CI = [1.351, 1.735], $p < 0.001$). Consequently, the interaction effect shows that the stickiness of positive emotions weakens in the absence of any emotion reminder (i.e., reporting condition).

Robustness

The results for the effect of positive emotion holds when we control for gender, age, race, employment status, marital status, education, natural log-transformed respondent income, reason category, self-control measure, and five main personality measures (B= 1.731, SE = 0.077, 95% CI = [1.581, 1.882], $p < 0.001$, β= 0.724), and the effect for tracking-annotate group holds marginally significant (B= -0.172, SE = 0.102, 95% CI = [-0.372, 0.028], p = 0.091, β= -0.125). The interaction effect also holds consistently (B= -0.440, SE = 0.167, 95% CI = [-0.767, -0.114], $p < 0.01$, β= -0.051).

Table 4 - Regression Results of Study 2: effect of annotated reminder on emotion stickiness

Variables	(1)	(2)	(3)	(4)
Positive Emotion	1.716***	1.866***	1.731***	1.936***
	(0.061)	(0.109)	(0.077)	(0.128)

Tracking-Annotate Condition	-0.128* (0.063)	-0.061 (0.139)	-0.172^ (0.102)	-0.077 (0.175)
Reporting Condition	-0.091 (0.061)	0.159 (0.128)	-0.123 (0.1)	0.218 (0.164)
Positive emotion * tracking-Annotate Condition		-0.087 (0.156)		-0.125 (0.177)
Positive emotion * Reporting Condition		-0.324* (0.146)		-0.44** (0.167)
Male			-0.13 (0.088)	-0.135 (0.088)
White			0.039 (0.097)	0.04 (0.097)
Employed			-0.031 (0.102)	-0.03 (0.102)
Married			0.14 (0.089)	0.145 (0.089)
4-Year College			0.132 (0.088)	0.137 (0.088)
Age			-0.002 (0.004)	-0.003 (0.004)
Natural Log Transformed Earnings			-0.009 (0.014)	-0.01 (0.014)
Self-Control			-0.057 (0.098)	-0.059 (0.098)

Extraversion			-0.004	-0.005
			(0.027)	(0.027)
Agreeableness			0.008	0.008
			(0.038)	(0.038)
Conscientiousness			-0.052	-0.051
			(0.037)	(0.037)
Stability			-0.136***	-0.137***
			(0.031)	(0.031)
Openness			-0.055	-0.056^
			(0.034)	(0.034)
Reason Category			Yes	Yes
Participants			Yes	Yes
Constant	-0.709***		0.414	0.283
	(0.065)		(0.451)	(0.458)
R^2	0.148	0.149	0.209	0.210

Notes: (1) The coefficients reported above are the unstandardized coefficients. (2) All numerical predictor variables are mean-centered.

^ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.3.5. Discussion

Study 2 further confirmed our results from Study 1. In general, positive emotions are stickier than negative emotions. When participants feel positive, it is more likely that the feeling sticks for the next day. Further, the effect of positive emotion stickiness is present regardless of the group assigned to participants.

Study 2 shows a (marginally) significant difference between the three groups. Notably, providing an emotional history paired with annotation (i.e., *tracking-annotate* group) decreased the likelihood of the current emotion to stick for the next day.

Finally, there is a significant interaction between emotion type and emotion reminder. Supporting Study 1 results, Study 2 shows that positive emotions are less sticky in the absence of any emotional reminder. That is if participants do not see any visualization of their emotional state history, the effect of positive emotion stickiness weakens. This result further supports our hypothesis that emotional tracking can improve mental health by facilitating positive emotion recall (H1).

2.4. General Discussion

Across disciplines, researchers have debated the importance of tracking people's physical and psychological well-being. While benefits of physical health tracking have been widely studied (Gordon et al., 2019; Higgins, 2016; Molina & Sundar, 2020; Payne et al., 2015), the benefits of tracking psychological states have received less attention. In this research, we showed that when people report their emotional state, it is more likely that the positive emotion persists for the next day compared to negative emotion.

More importantly, this effect is amplified in the presence of emotional reminder. People are very good at recalling their past negative experiences (Finn & Roediger, 2011; Kensinger, 2007, 2009). However, recalling the positive experiences and positive emotions they felt in the past is not always easy. Therefore, a tracking system that reminds people of their past positive emotions increases the chances that people feel positive the next day too.

2.4.1. Implications

These findings have three important implications. First, and most narrowly, the results speak to the persistence of emotional states. When people report their emotions and feelings, it is more likely for positive emotions (compared to negative emotions) to persist, and people feel positive the next day.

Second, the results highlight the difference in information gain for positive and negative emotions when people are provided with emotional states history. Prior research demonstrates that events associated with negative emotions are more easily recalled than events related to positive emotions (Finn & Roediger, 2011; Kensinger, 2009, 2009). Aligned with this notion, our results indicate that when people are reminded of their emotional state's history, the effect of positive emotion stickiness is amplified. This suggests that when people see their emotional state history, they are reminded of past days when they had a positive emotion, and they might recall the event which resulted in the positive feeling. Consequently, it boosts their current emotional state. A visualization reminder does not significantly affect the negative emotions because people naturally recall the negative events more easily.

Finally, and most importantly, the results shed light on possible future solutions and applications for improving people's psychological well-being. Prior research shows positive impacts of tracking objective measures, such as physical health. Extending this line of work, we show the positive effects of measuring subjective measures (such as emotional states) on people's well-being. Consequently, a digital emotional tracking platform, particularly one that provides a history of people's emotional states, would benefit people's psychological well-being. It encourages people to recall past positive events, which could therefore boost people's emotional state.

2.4.2. Conclusion

In conclusion, while a great deal of research has studied the benefits of tracking physical health, positive impacts of tracking psychological health (such as emotional states) remain understudied. Hopefully, this investigation will encourage researchers to further study this important topic and system designers to examine platforms for tracking people's psychological health.

2.5. Supplementary Analysis

2.5.1. Category Classification

One could wonder maybe the effect is driven by the reason behind a specific emotion and not the emotion itself. For example, if a participant feels negative because of a health issue, it could persist longer than the negative feeling caused by a bad day at work. To control for this possibility, we use deep learning to classify the reason participants feel a certain way and include the reason as a control variable in our model.

First, we start by creating our training set. Research assistants went through hundreds of text samples and extracted the main themes. Then, we set up a survey and recruited MTurk participants to categorize 1000 pieces of text into the predefined themes or enter a new category if the text does not fall into any of the existing categories. Coders were allowed to choose multiple categories, and for each piece of text, we collected at least three independent samples.
Second, we use factor analysis to discover categories that most often are selected together. In the end, we ended up with six major categories: health (short term or long term), work (including finances and goals as well), sleep, fun (including vacation, relationship, or any fun activity), future (including thinking about future and being spiritual), and none (no specific reason reported).

Third, we use BERT (Bidirectional Encoder Representations for Transformers, Devlin et al., 2019), an advanced deep learning model in natural language processing for classification.

BERT is trained on very large language datasets and learns contextual relations between words in text data. To fine-tune BERT for our classification task, we add a neural layer on top of the base model and train it with our training set. We achieved an accuracy of 80%. We then apply the trained model to our unlabeled text data and predict a category for each text.

Study 1

Robustness

One might wonder whether the way emotions were coded as positive and negative somehow drove the final results. As a robustness check, we coded emotions reported as 1, 2, and 3 as negative and 4, 5, 6, and 7 as positive. The results for positive emotion hold with the new definition of positive and negative emotions (N = 5163, $M_{positive}$ = 1.799, $SD_{positive}$ = 0.401, $M_{negative}$ = 1.286, $SD_{negative}$ = 0.452, $B_{positive\ emotion}$ = 2.304, SE = 0.102, 95% CI = [2.104, 2.504], $p < 0.001$, β= 0.887), but the results for reporting condition goes away ($M_{tracking}$ = 1.731, $SD_{tracking}$ = 0.443, $M_{reporting}$ = 1.693, $SD_{reporting}$ = 0.461, $B_{reporting\ condition}$ = -0.076, SE = 0.121, 95% CI = [-0.314, 0.162], p = 0.53, β= -0.056). The interaction between positive emotion and reporting condition also holds consistent ($B_{positive\ emotion*reporting\ condition}$ = -0.505, SE = 0.195, 95% CI = [-0.888, -0.123], $p < 0.01$, β = -0.126).

Some participants left the study early, while others completed the whole study and participated for 28 days. The results for positive emotion hold when a cutoff threshold of at least 75% is set on the participation days and all covariates are controlled for (N = 3964, $M_{positive}$ = 1.741, $SD_{positive}$ = 0.438, $M_{negative}$ = 1.296, $SD_{negative}$ = 0.457, $B_{positive\ emotion}$ = 1.921, SE = 0.112, 95% CI = [1.701, 2.141], $p < 0.001$, β = 0.766). However, the effect for reporting condition goes away ($M_{tracking}$ = 1.685, $SD_{tracking}$ = 0.465, $M_{reporting}$ = 1.633, $SD_{reporting}$ = 0.482, $B_{reporting\ condition}$ = -0.175, SE = 0.129, 95% CI = [-0.428, 0.078], p = 0.180, β= -0.090). The results for the interaction between positive emotion and reporting condition also hold consistent ($B_{positive\ emotion*reporting\ condition}$ = -0.499, SE = 0.211, 95% CI = [-0.913, -0.085], $p < 0.05$, β= -0.094).

Study 2

Robustness

One might wonder whether the way emotions were coded as positive and negative somehow drove the final results. As a robustness check, we coded emotions reported as 1, 2, and 3 as negative and 4, 5, 6, and 7 as positive. The effect for positive emotions holds consistent while controlling for other factors (N = 8895, $M_{positive}$ = 1.8, $SD_{positive}$ = 0.4, $M_{negative}$ = 1.309, $SD_{negative}$ = 0.462, $B_{positive\ emotion}$ = 2.267, SE = 0.074, 95% CI = [2.122, 2.413], $p < 0.001$, β= 0.896). However, the results for tracking annotate does not hold anymore ($M_{tracking}$ = 1.715, $SD_{tracking}$ = 0.452, $M_{tracking\ annotate}$ = 1.719, $SD_{tracking\ annotate}$ = 0.449, $M_{reporting}$ = 1.694, $SD_{reporting}$ = 0.461, $B_{tracking-annotate\ condition}$ = 0.009, SE = 0.099, 95% CI = [-0.185, 0.202], p = 0.928, β= -0.032, $B_{reporting\ condition}$= -0.088, SE = 0.097, 95% CI = [-0.278, 0.101], p = 0.362, β= -0.128). The results for the interaction between positive emotion and reporting condition also hold consistent ($B_{positive\ emotion*reporting\ condition}$ = -0.457, SE = 0.163, 95% CI = [-0.776, -0.138], $p < 0.01$, β= -0.064).

Some participants left the study early, while others completed the whole study and participated for 21 days. The results for positive emotion hold when a cutoff threshold of at least 75% is set on the participation days and all covariates are controlled for (N = 7066, $M_{positive}$ =1.732, $SD_{positive}$ =0.443, $M_{negative}$ = 1.316, $SD_{negative}$ = 0.465, $B_{positive\ emotion}$= 1.803, SE = 0.080, 95% CI = [1.647, 1.959], $p < 0.001$, β= 0.775). The results also stays the same for tracking-annotate condition ($M_{tracking}$ = 1.663, $SD_{tracking}$ = 0.473, $M_{tracking\ annotate}$ = 1.633, $SD_{tracking\ annotate}$ = 0.482, $M_{reporting}$ = 1.638, $SD_{reporting}$ = 0.481, $B_{tracking-annotate\ condition}$= -0.200, SE = 0.104, 95% CI = [-0.405, 0.004], p = 0.055, β= -0.133, $B_{reporting\ condition}$ = -0.095, SE = 0.103, 95% CI = [-0.298, 0.108], p = 0.359, β= -0.097). The results for the interaction between positive emotion and reporting condition also hold consistent ($B_{positive\ emotion*reporting\ condition}$ = -0.431, SE = 0.173, 95% CI = [-0.770, -0.092], $p < 0.05$, β= -0.049).

3. Living Link Lab: Occupant Behavior Research Testbed

The Living Link Lab provides a platform for research on occupants and indoor environments. Living Link Lab currently utilizes various sensors to monitor factors such as humidity, temperature, and motion (Figure 7). Integrating self-reporting and sensing in the Living Link Lab platform will enable us to compare the sensors' objective measurements against the participants' subjective reports. Comparing the subjective and objective measures allows us to investigate the relationships between participants' physical and mental states and verify our findings' external validity. Our study uses the Qualtrics survey framework to deliver smart and interactive surveys to our participants. These surveys can be combined with sensors, cameras, and digital feedback interfaces to expand the Living Link Lab's capabilities. We have implemented a system that delivers personal daily surveys for our participants while giving them full access to their shared data and privacy controls. This information will be processed to investigate the optimal feedback and intervention strategies to improve occupant’s subjective well-being and comfort, improve indoor environmental quality, and reduce energy consumption.

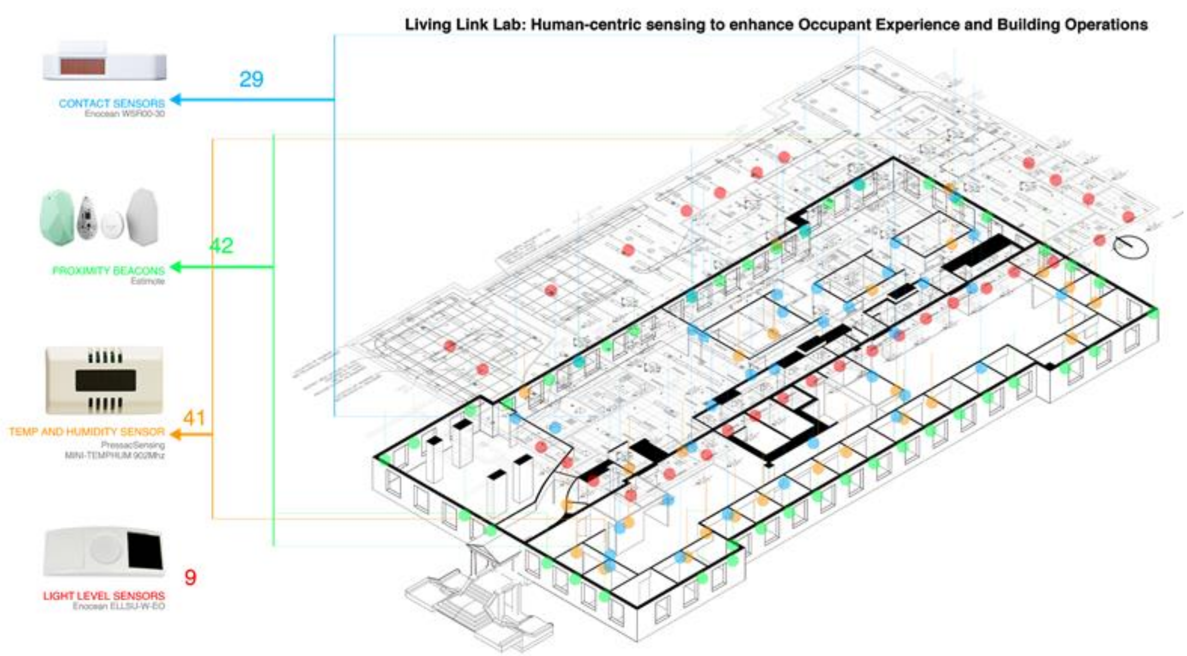

Figure 7 - Overview of the sensor arrangement in Living Link Lab

3.1. Implementation of Self-reporting System

The self-reporting system utilizes the Qualtrics API and survey templates to generate tailored surveys for the participants. These surveys will be distributed on the participants’ personal dashboard on the Living Link Lab website. Next, we retrieve and store the survey responses on the Living Link Lab database. Based on the experiments' design and requirements, this information can be visualized using Grafana and displayed on the participants' home page to provide longitudinal emotion tracking.

Through integration with Living Link Lab, the system administrators can design and publish surveys to perform experimental studies. The administrators can control the access of each participant to the existing surveys. To create a survey, the administrators create and add a main template to the Living Link Lab administrative control panel. Next, the participants, survey frequency (i.e., daily surveys), and whether the survey is optional or mandatory are selected. The Living Link Lab website uses the Qualtrics API to generate private surveys and access links for each participant. The components of the self-reporting architecture are discussed in the following.

3.1.1. Designing Surveys Using Qualtrics

Qualtrics is an online survey tool used to design and perform survey research and data collection. The extensive range of templates and design tools available in Qualtrics allows us to create surveys ranging from simple questionnaires to interactive surveys with complex conditions and workflow. Furthermore, the Qualtrics API and JavaScript functions will enable us to design surveys that can utilize Cloud Computing to process data and provide visualizations and feedback in real-time.

3.1.2. Real-time Retrieval and Data Visualization

Each survey uses an HTTP POST function to speed up the retrieval of the survey responses. This function immediately sends the survey responses back to the Living Link Lab server. The server then stores and processes the survey responses and sends the information to an InfluxDB time-series database. The Grafana visualization dashboard will use his data to update the visualizations in real-time.

Real-time Visualization Using Grafana

Behavioral studies design may require real-time visualization of the participant responses. To accomplish this, we have used the Django backend and the Grafana API to upload each user's data to a time-series database based on InfluxDB. Furthermore, the participants' personal Grafana dashboards will be updated to include the visualizations related to their survey responses.

3.1.3. Data Processing and Storage

The Living Link Lab website utilizes a Django backend to handle the Qualtrics API, data processing, data storage, and visualization. The Django modules are implemented using Python, Google Cloud Platform, and SQL.

3.1.4. Survey Templates

Survey templates create an easy way to scale our platform by automating the generation and distribution of surveys. To run surveys on the Living Link Lab, we design a template survey and add the survey ID to the administrator panel. We use the admin panel to assign the survey templates to the participants of the study. Next, Living Link Lab's backend will replicate the survey for each participant with a unique survey ID and access link. After the participants complete a survey, the survey links will be invalidated unless the "recurring" option is enabled. The "recurring" option is relevant to frequent surveys such as the daily surveys for subjective emotion tracking.

3.2. Implementation of Video Collection System

Our proposed video collection architecture utilizes Raspberry Pi 4 (RPi 4) compute units as personal edge devices for participants. Each participant will receive their own personal RPi 4 along with a Logitech C920 Full HD webcam. The RPi 4 devices record and encode the videos of the participants. Next, the processed video segments will be uploaded to a shared folder in UVa Box. This folder is only accessible by the user and the authorized research staff. We will download the video data on the personal UVa Box folders a week after their upload date. This gives the users at least seven days to review and remove any video information they do not wish to share. After seven days, the videos will be downloaded to a NAS in a secure location. This storage is securely encrypted, is not directly accessible through the internet, and requires a physical connection through a LAN cable. The details of the video collection components are provided in the following sections.

3.2.1. Online Video Storage

Sensitive user data, such as video data, cannot be stored on Google Drive. The University of Virginia policies dictate that we should store participants' video data on physical offline storage or the UVa Box for online storage. Finally, we want to give the participants the ability to filter their data both (1) before any data is collected and (2) review and delete their data once collected. Box facilitates this process as it provides a secure and online platform to share data with the participants.

We use the Box python SDK to manage and upload the videos to the personal folders of participants. We use the OAuth API to authorize our application to access the UVa box account. We are using OAuth 2.0 with user authentication since our application is too specific to be a general Box application and server-side authentication (JWT) was not possible. OAuth 2.0 requires an access token and a refresh token. We initially acquire these tokens for the Administrator account by authorizing access through a Google Cloud Function and a redirect URL from the Box website. The tokens generated through this method expire after 60 minutes but can be refreshed for up to 7 days. However, if both the access and refresh tokens expire, we need to reauthorize the program manually. Figure 8 documents the authentication workflow, and Figure 9 documents the credentials.

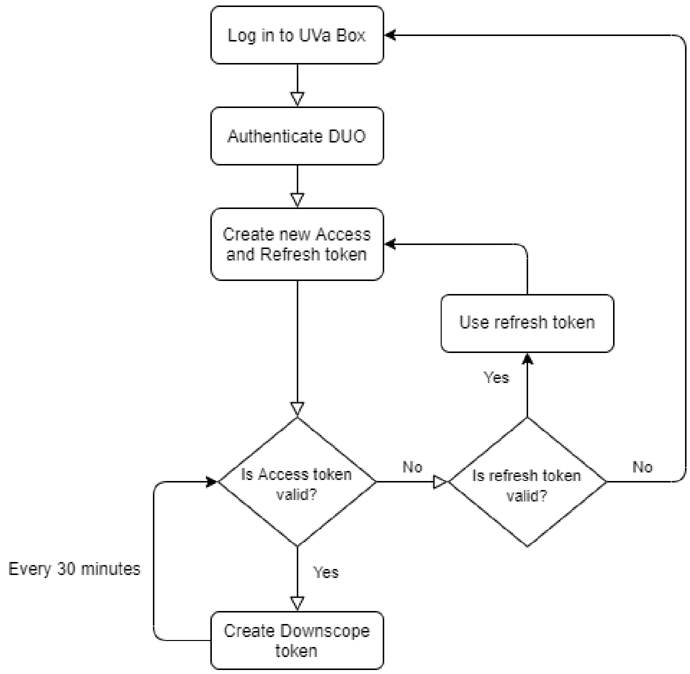

Figure 8 - UVa Box workflow

We will use the administrator account's Box credentials to create ‘Down-scoped Tokens’ for each participant. The down-scoped tokens limit the device access to a folder shared between the researchers and participants. This limited access means that users cannot use the credentials allocated to their device to access the data from other participants. Furthermore, the down-scoped tokens alleviate the need to access the participants' personal UVa Box account and protect participants' privacy against the researchers.

Credentials, expiration, and descriptions:

NAME OF CREDENTIAL	CREDENTIALS REQUIRED	RETRIEVAL	EXPIRES AFTER	DESCRIPTION
UVA Box Authentication	UVA login credentials	Using selenium (UVA, DUO)	1 week	Required for initial access
Access Token	UVA Box Authentication OR Refresh token	Generated using the web platform and DUO authentication OR using a refresh token	60 minutes	Required to use the API
Refresh Token	UVA Box Authentication OR Refresh token	Generated using the web platform and DUO authentication OR using the previous refresh token	Once used or 30 days	Required to refresh the access token
Downscoped Token	Access token	Program API	30 minutes	Required to ensure user privacy, limiting individual user scope

Figure 9 - UVa Box Credentials

3.2.2. Video Collection and Camera Actuation

The Raspberry Pi devices serve as the central hub to actuate the webcams, then record, encode, and upload the videos to UVa Box. Users can use the participant dashboard in Living Link Lab to control the video collection process. The Raspberry Pi devices connect to the Wahoo network and use a Read-only key to retrieve the UVa Box credentials and video recording settings. The key stored on each raspberry pi device is specific to the user and cannot access other participants' data and video settings.

3.2.3. Offline Video Storage

We use the QNAP TS-673-8G 6-Bay NAS and five 12TB hard disk drives running in a RAID 5 array. RAID 5 array allows the storage to function even if one of the drives fails. This redundancy, however, comes at the cost of storage space: The current setup's effective storage space is 48 Terabytes instead of 60 TB (five 12TB hard drives)

To store the videos of participants on the NAS, we use the FTP protocol and a Python script to access the UVa Box storage and downloads the available files. The script will run on a computer with a physical LAN connection to the NAS. We set up the update script to only download files uploaded more than seven days ago. The seven-day grace period will give the users enough time to delete their videos before the script downloads them to the NAS. We disconnect the NAS from the internet after downloading the data from Box. The data stored on the NAS can only be accessed with a physical connection to the NAS. Furthermore, we will encrypt the data with a secure passphrase to ensure the data cannot be compromised even with physical access to the storage array.

4. Discussion

The longitudinal experiments in this research have three important implications. First, and the results support the persistence of emotional states. When people report positive emotions and feelings, positive emotions are more likely to persist for the next day (compared to negative emotions).

Second, the results highlight the difference in information gain for positive and negative emotions when people are provided with their emotional states' history. Our results indicate that when people are reminded of their emotional state history, the effect of positive emotion stickiness is amplified. This suggests that when people see their emotional state history and are reminded of their positive emotions during past days, they might recall new information about the events, which resulted in positive feelings. Consequently, it boosts their current emotional state. The visualization reminder will have a weaker effect on the negative emotions, as people naturally recall the events more easily.

Finally, these results shed light on possible future solutions and applications for improving people's psychological well-being. Prior research shows positive impacts of tracking objective measures, such as physical health. Extending this line of work, we show the positive effects of measuring subjective measures (such as emotional states) on people’s well-being. Consequently, a digital emotional tracking platform, particularly one that provides a history of people’s emotional states without any further interventions, could benefit people’s psychological well-being. Emotional tracking encourages people to recall past positive events (which typically are forgotten) and therefore boosts their current and future emotional state.

4.1. Implications in Smart Buildings

Our review of the literature revealed gaps in emotion-sensing and emotion-aware buildings. As many individuals spend most of their lives indoors, emotion-sensing technologies in buildings can significantly improve the impact of the indoor environments on the occupants. Based on the findings of longitudinal experiments, we opted to design and implement a survey and video collection system to investigate the effects and applicability of emotion tracking in buildings. We have implemented a system that creates tailored daily surveys for our participants while giving them full access to their shared data and privacy controls. Furthermore, the participants can opt-in to share their video using the implemented video collection system. The video information will allow us to study the applications of machine learning and computer vision to emotion-sensing and behavior detection. The combination of self-reported surveys can be used as ground truth for supervised machine learning or verify the validity and accuracy of existing models. The video and survey collection system are integrated into the Living Link Lab testbed at the University of Virginia. The Living Link Lab serves as a real-life environment where the students and faculty at Link Lab can opt-in to share their data and participate in behavioral studies. This research's contributions combined with the existing sensor array and user interface of Living Link Lab provide an excellent opportunity to perform longitudinal studies on human behavior and well-being in the built environment.

Moreover, the interaction between occupant emotions and behavior means we need a deeper understanding of emotion tracking's impact on occupant behavior, performance, and comfort. Occupant behavior is the major contributing factor to variation in building energy consumption. Since building operations contribute to around a third of the energy consumption worldwide (International Energy Agency, 2020), any significant changes in buildings' energy consumption can significantly impact the environment. The multitude of goals such as improved emotions, increased comfort, enhanced productivity, and energy efficiency create a multi-objective problem. We can only address this multi-objective optimization by understanding the relationships between occupant emotions, behavior, performance, and indoor environment. The Living Link Lab testbed provides an invaluable infrastructure to study these factors and their relationships using subjective reports of the participants and the objective measurements of cameras, environmental sensors, and building management systems.

Finally, the implications of the emotion tracking system are not limited to built environments. Future works on emotion sensing in buildings can be coupled with sensing using smart wearables and personal devices to provide a more accurate emotion tracking system. However, user privacy, information security, and control over personal information are essential requirements that should be addressed for such a system. Different individuals may have different preferences for sharing their data, which can impact emotion tracking accuracy and efficacy. Furthermore, future work should focus on the legal and ethical issues of privacy and their implications for smart buildings and occupant tracking systems.

Appendix A

Questions Asked on the First Day of the Studies

Table 5 - Questions asked on the first day of the studies

Item	Question
ID	MTurk ID of the participant
Q40_1 Q40_2 Q40_3 Q40_4 Q40_5	To what extent did you experience the following during the past 4 weeks of your life? 1- Enjoyment 2- Happiness 3- Satisfaction 4- Stress 5- Worry
Q3_1 Q3_2 Q3_3 Q3_4 Q3_5	Below are five statements that you may agree or disagree with. Using the scale below, indicate your agreement with each item about your life now. 1- In most ways my life now is close to ideal. 2- The conditions of my life now are excellent. 3- I am satisfied with my life now. 4- So far I have gotten the important things I want in life now. 5- If I could live my life over, I would change almost nothing about my life now.
Q39	Please imagine a ladder with steps numbered from 0 at the bottom to 10 at the top. The top of the ladder represents the best possible life for you. If the top step is 10 and the bottom step is 0, on which step of the ladder do you feel you personally stand at the present time?
Q38_1 Q38_2 Q38_3 Q38_4 Q38_5 Q38_6 Q38_7 Q38_8 Q38_9 Q38_10 Q38_11 Q38_12 Q38_13	This scale consists of a number of words that describe different feelings and emotions. Indicate to what extent you have felt the following over the past 4 weeks of your life: 1. Interested 2. Distressed 3. Excited 4. Upset 5. Strong 6. Guilty 7. Scared 8. Hostile 9. Enthusiastic 10. Proud 11. Irritable

Q38_14	12. Alert
Q38_15	13. Ashamed
Q38_16	14. Inspired
Q38_17	15. Nervous
Q38_18	16. Determined
Q38_19	17. Jittery
	18. Active
Q38_20	19. Afraid
Q36_1	Here are a number of personality traits that may or may not apply to you. Please indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.
Q36_2	1. Extraverted, enthusiastic
Q36_3	2. Critical, quarrelsome
Q36_4	3. Dependable, self-disciplined
Q36_5	4. Anxious, easily upset
Q36_6	5. Open to new experiences, complex
Q36_7	6. Reserved, quiet
Q36_8	7. Sympathetic, warm
Q36_9	8. Disorganized, careless
	9. Calm, emotionally stable
Q36_10	10. Conventional, uncreative
Q10	I am good at resisting temptation.
Q12	I have a hard time breaking bad habits.
Q14	I am lazy.
Q16	I say inappropriate things.
Q18	I do certain things that are bad for me, if they are fun.
Q20	I refuse things that are bad for me.
Q22	I wish I had more self-discipline.
Q24	People would say that I have iron self- discipline.
Q26	Pleasure and fun sometimes keep me from getting work done.
Q28	I have trouble concentrating.
Q30	I am able to work effectively toward long-term goals.
Q32	Sometimes I can't stop myself from doing something, even if I know it is wrong.
Q34	I often act without thinking through all the alternatives.
Q57#1_1_1	How much on average do you listen to music everyday? - Hours, Minutes - Amount of time you listen to music every day
Q57#1_1_2	

	Hours Minutes
Q58#1_1_1 Q58#1_1_2	How much on average do you have physical activity in a day? - Hours, Minutes - Amount of time you have physical activity every day - Hours - Minutes
Q59#1_1_1 Q59#1_1_2	On average, how many hours a day do you use your smartphone? - Hours, Minutes - Amount of time you use your smartphone every day - Hours - Minutes
Q60#1_1_1 Q60#1_1_2	On average, how often do you socialize with others daily? - Hours, Minutes - Amount of time you socialize with others daily - Hours - Minutes
Q61#1_1_1 Q61#1_1_2	How often do you spend outdoors daily? - Hours, Minutes - Amount of time you spend outdoors daily - Hours - Minutes
Q63#1_1_1 Q63#1_1_2	On average, how many hours of sleep do you get at night? - Hours, Minutes - Amount of sleep you get at night - Hours - Minutes
Q55	Do you track your fitness goals (e.g., tracking steps)?
Q23	How much free time do you have these days?
Q25	What is your current employment status? - Selected Choice
Q25_6_TEXT	What is your current employment status? - Other - Text
Q27#1_1_1 Q27#1_1_2	During a typical week, approximately how much time do you work in a job for which you get paid? P... - Hours, Minutes - Amount of time you work per week - Hours - Minutes
Q29	What is/ was your occupation?
Q31	What is the highest educational degree you have earned?
Q33	How much do you personally make each year (in $)? If you do not earn a personal income, write 0.
Q35	What is your annual household income?
Q37	Are you married?

Q39	Do you have children?
Q41	How many children do you have? Enter 0 if you don't have any children.
Q43	How many of your children live with you full time? If none of your children live with you, write 0.
Q47	What is your gender?
Q49	What is your age?
Q51	What is your ethnicity? - Selected Choice
Q51_6_TEXT	What is your ethnicity? - Other - Text
Q33	Today is the last day of the study. You will first be asked about how you are feeling today. Afte...

Questions Asked on the Final Say of Study 1

Table 6 - Questions asked on the final day of study 1

Item	Question
Q33	Why do you feel this way?
Q35	Can you write down the main reason you feel this way in a few words? (15 characters max)
Q11	This is the last day of the study. You will be asked a few additional questions on the next page.
LC	Think about your emotions over the past three weeks.Â Â Was the cause of your emotions over the p...
Q16	Was the cause of your emotions over the past four weeks something that reflects an aspect of you...
Q17	Was the cause of your emotions over the past four weeks something temporary or something permanent?
Q18	Was the cause of your emotions over the past four weeks something you could regulate?
Q19	Was the cause of your emotions over the past four weeks something over which others had control?
LC	Was the cause of your emotions over the past four weeks outside of you or inside of you?
Q21	Was the cause of your emotions over the past four weeks stable over time?
Q22	Was the cause of your emotions over the past four weeks under the power of other people?
Q24	Was the cause of your emotions over the past four weeks something about you?
Q25	Was the cause of your emotions over the past four weeks something over which you have power?
Q26	Was the cause of your emotions over the past four weeks unchangeable?
Q27	Was the cause of your emotions over the past four weeks something which other people could regul...
Q3_1	To what extent did you experience the following during the past 4 weeks of your life? -Enjoyment
Q3_8	To what extent did you experience the following during the past 4 weeks of your life? -Happiness
Q3_2	To what extent did you experience the following during the past 4 weeks of your life? -Satisfaction
Q3_13	To what extent did you experience the following during the past 4 weeks of your life? -Stress
Q3_14	To what extent did you experience the following during the past 4 weeks of your life? -Worry
Q5_1	Below are five statements that you may agree or disagree with. Using the scale below, indicate yo...-In most ways my life now is close to ideal.
Q5_8	Below are five statements that you may agree or disagree with. Using the scale below, indicate yo...-The conditions of my life now are excellent.

Q5_2	Below are five statements that you may agree or disagree with. Using the scale below, indicate yo...-I am satisfied with my life now.
Q5_3	Below are five statements that you may agree or disagree with. Using the scale below, indicate yo...-So far I have gotten the important things I want in life now.
Q5_12	Below are five statements that you may agree or disagree with. Using the scale below, indicate yo...-If I could live my life over, I would change almost nothing about my life now.
Q7	Please imagine a ladder with steps numbered from 0 at the bottom to 10 at the top. The top of the...
Q9_1	This scale consists of a number of words that describe different feelings and emotions. Indicate… 1. Interested 2. Distressed 3. Excited 4. Upset 5. Strong 6. Guilty 7. Scared 8. Hostile 9. Enthusiastic 10. Proud 11. Irritable 12. Alert 13. Ashamed 14. Inspired 15. Nervous 16. Determined 17. Attentive 18. Jitterry 19. Active 20. Afraid
Q9_2	
Q9_3	
Q9_4	
Q9_5	
Q9_6	
Q9_7	
Q9_8	
Q9_9	
Q9_10	
Q9_11	
Q9_12	
Q9_13	
Q9_14	
Q9_15	
Q9_16	
Q9_17	
Q9_18	
Q9_19	
Q9_20	
Q10	How much did you enjoy participating in this study?
Q8	Feel free to leave any comments about the study below. This is optional.

Questions Asked on the Final Say of Study 2

Table 7 - Questions asked on the final day of study 2

Item	Question
Q33	Why do you feel this way?
Q35	Can you write down the main reason you feel this way in a few words? (15 characters max)
Q11	This is the last day of the study. You will be asked a few additional questions on the next page.
LC	Think about your emotions over the past three weeks.Â Â Was the cause of your emotions over the p...
Q16	Was the cause of your emotions over the past three weeks something that reflects an aspect of you...
Q17	Was the cause of your emotions over the past three weeks something temporary or something permanent?
Q18	Was the cause of your emotions over the past three weeks something you could regulate?
Q19	Was the cause of your emotions over the past three weeks something over which others had control?
LC	Was the cause of your emotions over the past three weeks outside of you or inside of you?
Q21	Was the cause of your emotions over the past three weeks stable over time?
Q22	Was the cause of your emotions over the past three weeks under the power of other people?
Q24	Was the cause of your emotions over the past three weeks something about you?
Q25	Was the cause of your emotions over the past three weeks something over which you have power?
Q26	Was the cause of your emotions over the past three weeks unchangeable?
Q27	Was the cause of your emotions over the past three weeks something which other people could regul...
Q3_1	To what extent did you experience the following during the past 3 weeks of your life? -Enjoyment
Q3_8	To what extent did you experience the following during the past 3 weeks of your life? -Happiness
Q3_2	To what extent did you experience the following during the past 3 weeks of your life? -Satisfaction
Q3_13	To what extent did you experience the following during the past 3 weeks of your life? -Stress
Q3_14	To what extent did you experience the following during the past 3 weeks of your life? -Worry
Q5_1	Below are five statements that you may agree or disagree with. Using the scale below, indicate yo...-In most ways my life now is close to ideal.
Q5_8	Below are five statements that you may agree or disagree with. Using the scale below, indicate

	yo...-The conditions of my life now are excellent.
Q5_2	Below are five statements that you may agree or disagree with. Using the scale below, indicate yo...-I am satisfied with my life now.
Q5_3	Below are five statements that you may agree or disagree with. Using the scale below, indicate yo...-So far I have gotten the important things I want in life now.
Q5_12	Below are five statements that you may agree or disagree with. Using the scale below, indicate yo...-If I could live my life over, I would change almost nothing about my life now.
Q7	Please imagine a ladder with steps numbered from 0 at the bottom to 10 at the top. The top of the...
Q9_1	This scale consists of a number of words that describe different feelings and emotions. Indicate…
Q9_2	
Q9_3	21. Interested
Q9_4	22. Distressed
Q9_5	23. Excited
Q9_6	24. Upset
Q9_7	25. Strong
Q9_8	26. Guilty
Q9_9	27. Scared
Q9_10	28. Hostile
Q9_11	29. Enthusiastic
Q9_12	30. Proud
Q9_13	31. Irritable
Q9_14	32. Alert
Q9_15	33. Ashamed
Q9_16	34. Inspired
Q9_17	35. Nervous
Q9_18	36. Determined
Q9_19	37. Attentive
	38. Jitterry
	39. Active
Q9_20	40. Afraid
Q10	How much did you enjoy participating in this study?
Q8	Feel free to leave any comments about the study below. This is optional.

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