Koan: A multimodal emotion prediction wearable for improved digital wellbeing

Every day, billions of us spend hours on our laptops, smartphones and other devices. While these technologies are incredibly useful, many systems impose emotional and cognitive costs. Like slot machines, some are designed to exploit inherent psychological biases to maximise and monetise user attention. Consequently, many feel a loss of agency over their technology use, a feeling often linked with poor subjective wellbeing. This report proposes Koan, an emotion prediction ring-wearable that helps users understand the relationship between digital behaviours and emotions. It motivates behaviour change relating to digital wellness by overlaying technology use with affective data and making evidence-based recommendations to the user.

Author Keywords: Wearables; affective computing; digital wellbeing; user engagement; just-in-time interventions; meaningful interaction

ACM Classification Keywords: H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

1 INTRODUCTION

Koan—a teaching in the practice of Zen Buddhism to invoke the exploration of the inner workings of the mind [1].

There is no denying that technology has fundamentally changed how humans work, play and rest, making us more creative, connected and productive. However, motivated by an industry that prioritises user growth, technology companies employ a range of design mechanisms—such as never-ending newsfeeds, eye-catching content and constant notification delivery—to maintain user attention [2]. In recent years, technologists have voiced concerns that many of these services exploit vulnerabilities in human psychology [3, 4]. These techniques make it difficult for users to focus on their current task and avoid the constant influx of notifications and habitual check-ins [5, 6, 7, 8]. It may then come as no surprise that compulsive internet use is frequently linked with a loss of agency, which is a key component of several problematic technology use measures [9, 10].

Digital wellbeing has emerged as a term to describe the extent to which a person perceives their technology use to be aligned with their long-term goals [11]. Researchers in this space have developed digital wellbeing tools, using techniques like self-monitoring screen time and removing or blocking access to distracting functionality [12, 13, 14]. Despite recent efforts from the tech giants [11, 15], the relationship between screen time and wellbeing measures is still unknown [16]. The key ingredient missing from these tools is understanding how one's emotional state relates to technology use. Emotions are complex and dynamic processes that can have a range of beneficial and detrimental long-term health consequences. For example, happiness correlates with greater longevity, while stress can increase susceptibility to infection and illness [17, 18]. As technology adoption increases—the time spent online has doubled in the last decade [19]—there is a growing need for a system that helps people understand which digital activities have the most influence over emotional state.

In this paper, I present Koan, an emotion prediction ring-wearable that enables better self-management of digital behaviours and improves general wellbeing.

2 RELATED WORK

My proposed technology builds on related work in wearable emotion trackers, deep learning methods and behaviour change technologies.

2.1 Wearable Emotion Trackers

Recent innovations in wearable technologies have made it possible to collect high-resolution data in a non-invasive way [20]. The wearable market is flooded with devices that provide support and advice relating to physical activity, physiological monitoring, and to a lesser extent, emotional monitoring (e.g. [21, 22, 23, 24, 25, 26]). Large firms like Amazon, Microsoft and Fitbit, along with newcomers Upmood and Moodmetric, have begun developing emotion recognition and stress management tools [27, 28, 29, 30, 31].

Physiological and emotional state are measured via various signals, including heart rate (HR), heart rate variability (HRV), body temperature, respiration rate, and electrodermal activity (EDA) [32]. EDA refers to slight

changes in the skin's electrical activity such as sweating, blood pressure changes, and hair follicle elevation [33]. Physiologists describe it as the most effective correlate for determining emotional arousal [34].

Due to sensor and battery technology limitations, wearables that measure EDA are generally large, bulky wrist-worn devices (e.g. Empatica E4 [35]). Moodmetric is developing a smaller ring-wearable that provides real-time feedback on emotional state [31]. However, a fundamental limitation of the device is that emotions are inferred from a single physiological modality. Previous work suggests that multimodal emotion prediction technologies are more accurate than their unimodal counterparts [36]. Based on these insights, Koan combines data from multiple modalities.

2.2 Predicting Emotions

As wearables become more accurate, the goal of forecasting emotions becomes more of a reality [37, 38, 39]. Researchers have used deep learning methods such as long short-term memory (LSTM) neural networks to predict stress, mood and physical health with striking accuracy. Taylor et al. [37] trained personalised models using today's physiological and behavioural data to forecast tomorrow's wellbeing (good-poor stress and mood) with 78-82% accuracy. In a follow-up study, Umematsu et al. [38] predicted stress without using personalised prediction models. They used LSTM neural networks to forecast tomorrow's high-low stress using seven days of time-series multimodal data [38]. Further work has predicted tomorrow's affective state on a scale of 0-100 using automated regression algorithms and physiological data gathered between 10 am and 5 pm the previous day [39].

The predictions made by these algorithms are limited to mood, stress and physical health. My proposed technology addresses this limitation by forecasting specific emotions and their valance, duration and intensity. Many of today's emotion-sensing systems are based on Ekman's [40] six basic emotions (e.g. [41, 42, 28]). Koan extends these technologies by using Plutchik's Wheel of Emotions which includes eight core emotions [43]. These emotions increase and decrease in intensity to produce one of sixteen secondary emotions (see Figure 1).

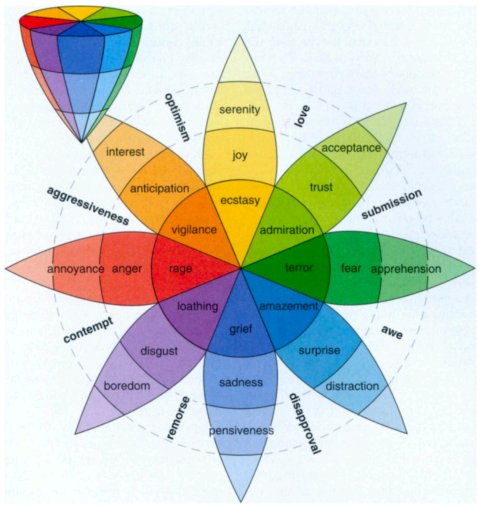

Figure 1: Plutchik's Wheel of Emotions [43].

2.3 Digital Behaviour Change Interventions

Since Koan is a tool that assists in behaviour change, understanding how behaviour change technologies work is relevant for the present paper. Digital Behaviour Change Interventions (DBCIs) are technologies that encourage desirable changes in behaviour by reinforcing certain habits and beliefs [44, 45, 46]. Underlying many of these applications is COM-B, a psychological model for explaining human behaviour [47]. The model posits that behaviours are produced by influencing one or more of the following: capability, opportunity and motivation (see Figure 2). Capability refers to whether individuals have the knowledge and skills required to engage in an activity. Motivation is the mental energy that influences behaviours and decision-making. Opportunity includes the external factors that enable or prompt the behaviour. A COM-B analysis was

conducted to identify common barriers to improving digital wellbeing; examples are provided in the next section.

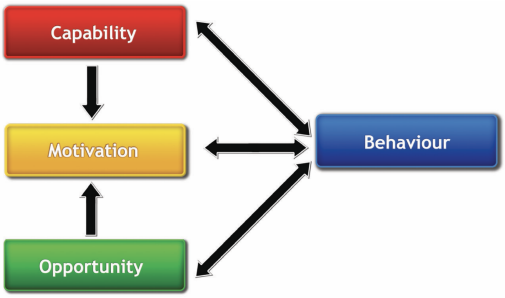

Figure 2: The COM-B model [47].

3 KOAN

3.1 People, Activities, and Contexts

Koan is an emotion prediction system composed of a ring-wearable and companion smartphone and desktop applications. The system is aimed at anyone who spends prolonged periods using technology. However, it is especially helpful for people who experience cognitive failures and poor subjective wellbeing from excessive technology use [48, 49].

Koan increases the user's capability to improve digital wellbeing by drawing attention to the relationship between emotions and device usage. Affective data is overlayed with technology use in a self-monitoring dashboard (see Figure 3). Koan will highlight trends between digital behaviours and emotions, helping users uncover harmful patterns of behaviour. Based on these insights, the system will make evidence-based recommendations. For example, a user who is frequently annoyed during moments when they receive several email notifications, perhaps while trying to concentrate on something important, may benefit from limiting email checking. Studies show that reducing email checking can reduce stress, increase productivity, and improve general wellbeing [50, 51]. Critically, Koan enables users to monitor whether the recommended change in behaviour affects their emotional state, motivating them to stick with the new behaviour or try something else.

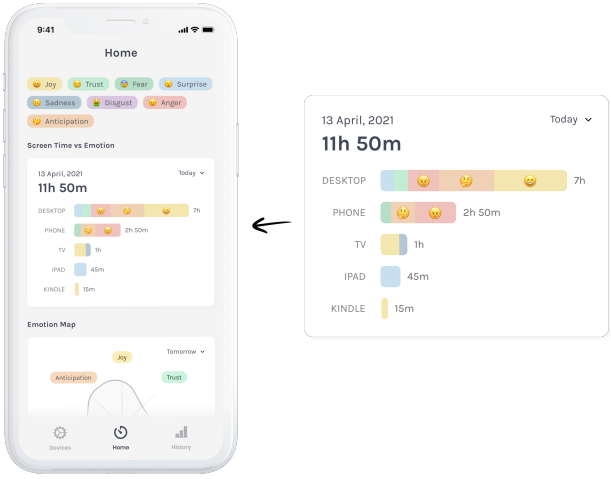

Figure 3: Self-monitoring dashboard on mobile.

The system creates opportunities to improve digital wellbeing by delivering just-in-time adaptive interventions. These nudges are tailored to the immediate and changing needs of the user. For instance, if Koan predicts a fast-approaching moment of boredom, it will recommend taking a break (see Figure 4). Research

suggests that going for a walk can improve mood, boost productivity, and enhance creativity [52, 53]. Again, users are encouraged to monitor how the behaviour change influences their emotions.

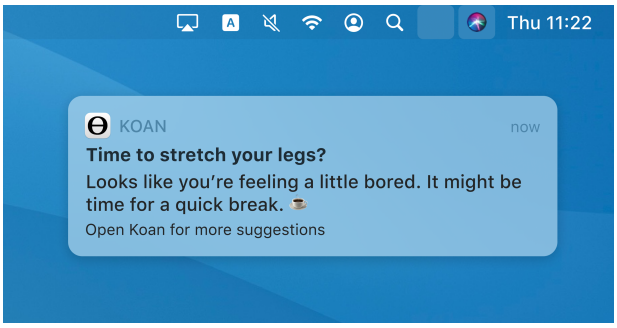

Figure 4: Just-in-time intervention desktop notification.

3.2 Technology

The Koan ring comprises multiple sensors that measure high-resolution physiological data (see Figure 5). EDA, measured as skin conductance and skin temperature, is used to determine sympathetic nervous activity [33, 54]. A 3-axis accelerometer tracks step counts and stillness, both of which correlate to emotional arousal [38]. Blood volume pulse is extracted via a photoplethysmography sensor from which HR and HRV can be derived [55]. Each of these sensors already exists today; however, due to battery requirements and limitations in their size, it is not currently possible to fit them onto a single wearable ring. Koan's subtle and compact form factor relies on advances in battery and micro-sensor technologies.

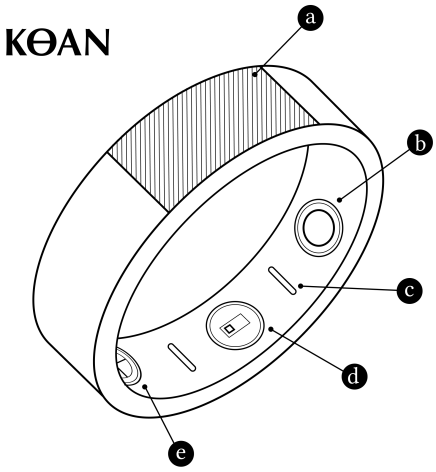

Figure 5: Ring schematic. a) miniature touch-enabled display, b) photoplethysmography sensor, c) induction charging coil, d) 3-axis accelerometer, e) EDA sensor

A miniature touch-enabled display, located on the ring, allows users to view the information most important to them (see Figure 6). Data is displayed in a duo-tone minimalist design to maximise visual acuity. Previous work notes that miniature displays can present several interaction challenges for wearable devices [56]. Consequently, the touch interaction is constrained to a single swipe across the screen which cycles between data options. Micro-animations signal this action to first-time users; the data will bounce slightly from left to right, prompting a swipe. Alternatively, the display settings can be adjusted via the smartphone and desktop applications.

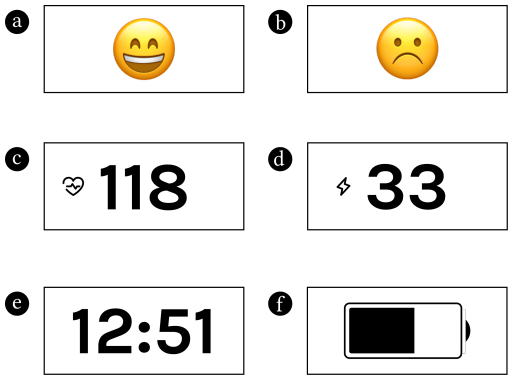

Figure 6: Ring display examples. a) joy, b) sadness, c) HRV, d) stress score, e) time, f) battery indicator

Koan integrates with popular consumer devices (e.g. phones, laptops, desktops, smart TVs and smart speakers) to track technology usage. The data is displayed to users in a self-monitoring dashboard, showing them when and for how long they used each device or application. Koan also collects social activity and mobility data. Recent work suggests that the level of social support in one's life has a strong connection to certain emotions [57, 58]. Moreover, studies show that affective state can be accurately inferred from a user's mobility patterns [59, 60].

Physiological, social, and mobility data are fed into a LSTM neural network which predicts current and future affective state (see Figure 7). While the model needs only a few hours of data capture to make a prediction, accuracy improves as more data is collected.

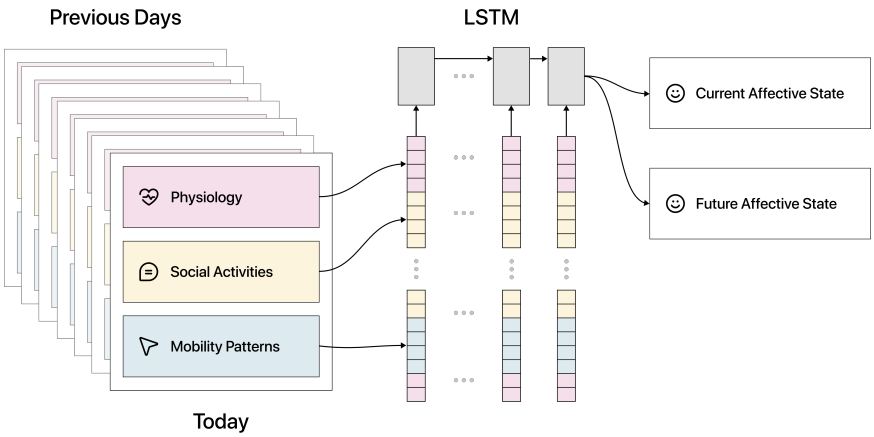

Figure 7: Overview of the Koan algorithm.

4 PERSONA AND SCENARIO

Charlotte is a 32-year old stockbroker living in New York City. She juggles a busy schedule, constantly moving between meetings, researching the financial markets, and pitching to new clients. Recently, she has felt down in the dumps and is struggling to understand why. She is interested in tracking her emotions to see what can be done to improve how she feels.

The day is coming to an end, and Charlotte is figuring out tomorrow's schedule (see Figure 8a). She closes her calendar and opens the Koan desktop app (b). The system predicts that she will likely feel annoyed, apprehensive and a little sad tomorrow morning. A recommendation beside this insight reads: "You usually spend the first 15 minutes of the day in bed, checking the news, and scrolling through Instagram. Why not try reading a book or going for a walk instead?" The following morning she reluctantly reaches for her Kindle instead of her phone (c). A few hours later, on her way to work, Charlotte notices a spring in her step (d). Curious about whether her emotional state was different than usual this morning, she checks the Koan

smartphone app (e). Sure enough, joy, interest, and serenity were spiking all morning, even after she had finished reading. Several days later, after a few more mornings like this, Koan notifies Charlotte that her emotional state has significantly improved since she stopped using her phone first thing in the morning (f). This information reinforces the positive behaviour, motivating Charlotte to stick with her new morning habit.

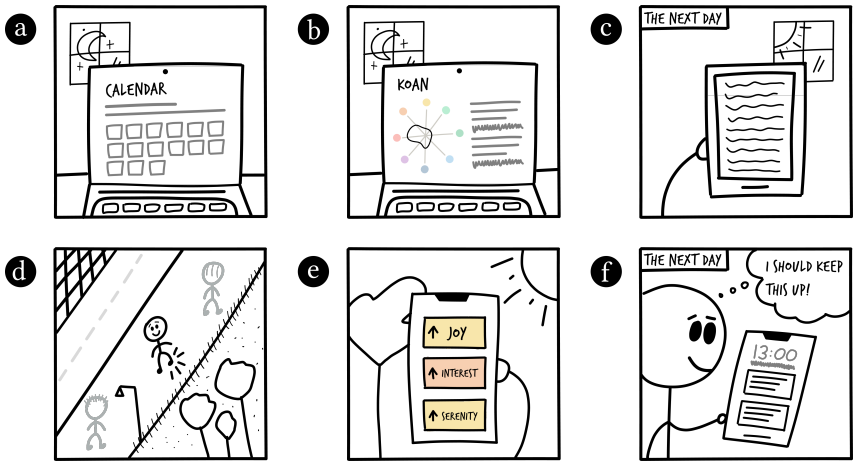

Figure 8: Scenario storyboard.

5 PLAN FOR EVALUATION AND SUCCESS CRITERIA

Koan aims to improve wellbeing by informing users about the relationship between technology use and emotions. Thus, I propose a mixed-methods evaluation study assessing (i) whether using Koan affects psychological wellbeing and (ii) if users learn anything from the experience. The study will take place over three weeks. In the first week (baseline phase), participants will be instructed to use their devices as normal. During the second and third weeks (experimental phase), participants will be randomly assigned to either continue using technology as normal or to use Koan. Subjects will self-report measures of psychological wellbeing at the end of each day throughout the study. Wellbeing measures could include mood, positive and negative affect (i.e. happiness), stress, anxiety, inattention, and social connectedness. Following the completion of the study, post-experiment interviews will be conducted. The main topics probed will be (i) whether Koan functioned as intended, (ii) what participants learnt from the intervention, and (iii) why participants thought the intervention was a success or failure.

A limitation of this method is that the intervention lasts for only two weeks. A follow-up study could address this drawback by investigating the long-term effectiveness of using Koan as a means to improve wellbeing.

6 BENEFITS, CONTRIBUTION AND LIMITATIONS

Technology companies make decisions based on economic incentives rather than user wellbeing or societal benefit. Motivated by shareholder commitments, profits are generated by increasing user engagement, resulting in a mismatch between user goals and creator goals. The main contribution of the present work is a ring-wearable that provides users with the tools to bridge this divide and regain control of their technology use.

6.1 Limitations

Multiple Arousal Theory. In some cases, depending on which neurological system of the brain is activated, EDA measurements can vary between left and right hands [61]. To address this challenge, Koan could encourage users to trial the ring on each hand for one day and then inform them which side is exhibiting the strongest response.

Discrete Emotion Model. Based on a discrete emotion model, the Koan algorithm classifies emotions into distinct categories [43]. While such models allow for a clear differentiation between affective states, they cannot

easily capture mixed states. A future iteration of the algorithm could experiment with a hybrid approach where emotions are mapped onto a dimensional space (e.g. [62, 63]).

Self-fulfilling Effects. Research suggests that receiving feedback from an emotion-sensing technology can significantly influence a user's perceived emotional state [64]. Future work might investigate the most appropriate way for Koan to frame affective data to avoid these self-fulfilling effects.

7 ETHICAL CONSIDERATIONS

A critical ethical concern of any affect detection system is the potential for emotional control and manipulation [65, 66]. For instance, marketers could use emotional data to accurately target moments when consumers are most vulnerable to advertising. Previous work has shown that people are most likely to spend money when they are sad [67]. A more concerning example is a totalitarian government that uses emotional data to identify and incarcerate dissidents [68]. As a new entrant to the affective computing space, Koan must build trust by assuring users that data will be safely stored and informing them about why data is being collected. This goal could be achieved by storing data in a privacy-preserving blockchain, giving users complete control over their data through private keys [69].

8 FUTURE WORK

While the focus of this work is on improving digital wellbeing, Koan has many other use cases. Several mental and physical conditions manifest physiologically long before a diagnosis can be made. For instance, patients who experience depressive symptoms often describe a reduction in energy and happiness stretching back long before they first sought medical advice [70]. A future application of Koan could provide users with warning signs, helping them receive treatment early and prevent severe disorders.

9 CONCLUSION

In this paper, I have presented a novel emotion prediction wearable that liberates users from the forces of intelligent, persuasive design. While current approaches to digital wellbeing focus on reducing overall screen time, Koan helps users distinguish between healthy and harmful technology use. The system combines high-resolution multimodal data with deep learning methods to forecast emotions, enabling better self-management of behavioural choices. Ultimately, Koan acts as an exoskeleton for the mind, which puts user values, not impulses, first.

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