How are you feeling? Using Tangibles to Log the Emotions of Older Adults

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ABSTRACT

The global population is ageing, leading to shifts in healthcare needs. Home healthcare monitoring systems currently focus on physical health, but there is an increasing recognition that psychological wellbeing also needs support. This raises the question of how to design devices that older adults can interact with to log their feelings. We designed three tangible prototypes, based on existing paper-based scales of affect. We report findings from a lab study in which participants used the prototypes to log the emotion from standardised emotional vignettes. We found that the prototypes allowed participants to accurately record identified emotions in a reasonable time. Our participants expressed a perceived need to record emotions, either to share with family/carers or for self-reflection. We conclude that our work demonstrates the potential for in-home tangible devices for recording the emotions of older adults to support wellbeing.

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CCS CONCEPTS

• **Human-centered computing → Interaction devices**.

KEYWORDS

Older adults; Emotion; Affect; Mood; Wellbeing; TUI

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1 INTRODUCTION

Across the globe, populations are ageing. The UN expects the number of older adults[1] to increase from 962 million globally in 2017 to 2.1 billion in 2050 and 3.1 billion in 2100 [36]. This increase in the age of the population has huge implications for healthcare. If no other factors change, such a shift will

[1]For the purposes of this work, we use the term 'older adults' to refer to anyone over the age of 60 based on the recommendations of Age UK (the main charity working with older adults in the UK).

lead to an increasing number of people with long-term disabilities and chronic conditions. This will increase the need for carers, and will likely increase the costs of healthcare [54]. From both cost-efficiency and wellbeing perspectives, there is a general need to facilitate people's ability to 'age in place' (i.e. at home) [35].

There have been promising developments in the design of technology to support an ageing population, particularly automated systems for managing home care technologies [26] or coordinating interactions with home care support teams [2]. Reviews of technologically assisted care indicate several partially successful implementations of systems, particularly with smart homes using activity detection, medication adherence, and other behavioural monitoring [3].

To date, much of the focus of this monitoring has been task- or health-specific; studying either an individual's activities (e.g. showering or eating) [3] or elements of the individual's health (blood pressure; heart rate; whether they have fallen over) [1]. However, with a clear link between 'successfully' ageing, physical health and wellbeing, there is an increasing focus on how to support the psychological wellbeing of older adults [53]. In a smart home scenario, this necessitates some mechanism for the detection or logging of the older adult's affective state to either ensure that the older adult is happy, or, when in emotional turmoil, appropriate support can be structured [10, 32, 50]. Such a logging system should not be passive but should be actively used by participants so that the older adult's privacy is retained and they gain the benefits of engaging with a system that is inferring about their health and wellbeing [25, 42].

The vast bulk of interfaces developed to monitor affect have tended to focus on younger people [8, 9, 15, 17, 19, 20, 29, 43, 49]. These interfaces may not be immediately adaptable to use by older adults who have distinct cognitive, physical and technical skills, alongside distinct wellbeing needs [53]. Therefore it is necessary for us to consider how to develop a mechanism for recording the affective state of older adults at home over a long period of time.

In this paper we present a study to develop an interactive tangible device for older adults to record their emotions. We designed a series of paper prototypes and examined their validity against existing scales of emotion. Our findings show that the paper prototypes allowed participants to accurately record identified emotions. The results also highlight that our participants expressed a perceived need to record emotions, either to share with family/carers or for self-reflection, with this need influencing the participants' preference of device. This demonstrates the potential for in-home tangible devices for recording the emotions of older adults.

2 LITERATURE REVIEW

Across all fields interested in affective experience, there are three main approaches to detecting and measuring how people feel; physiological, behavioural cues and self-report.

Under the physiological approach, a person's physiological state is measured and the affective state is inferred, through parameters such as blood pressure, heart rate or galvanic skin response [39].

The second approach to detecting affect is to examine behavioural cues, based on the concept that certain affective states are reflected in behavioural tendencies [11]. Techniques include coding facial expressions [52], detecting smiles from public cameras [16], inferring mood from signals present in video blogs [48] or inferring mood through activity on social media [28] or mobile phone use [21].

While both techniques show promise, they also remove the agency of the person whose affective state is being inferred. The third approach to detecting affect is self-reporting. This approach uses scales and measures based on theoretical constructs of emotion. These scales are completed by an individual, providing a score for their current affective state. The main limitations for self-reporting are well known; generally, such scales cannot provide continuous monitoring and are biased by a respondents' ability and willingness to report on their feelings [40].

While self-report measures have shortcomings, they provide the user with a level of control over the disclosure of their affective state which is important for older adults in having an active role in their healthcare needs [25, 42].

There is a rich literature on the benefits to an individual of emotional reflection and recording, which is commonly used as a therapeutic technique [38]. A recent review of ecological momentary assessment of mood highlights the importance of self-reporting due to ecological validity and agency [58]. From a technology perspective, studies are starting to show how technologically-mediated reflection and recording can improve wellbeing [22] and promote behaviour change [18].

Self-reported emotion scales

There are dozens of different measures and scales focussed on affect in the psychology literature (see [9] for an excellent review). It has become common for such measures to coalesce around two concepts: pleasure (or affect) and valence. Dominance is a common third concept [5]. The theory is that these three dimensions can account for significant variances in people's emotional experiences.

Russell has been a strong proponent of a two-dimensional approach to conceptualizing affect, demonstrating how a range of models of affect can be presented as a spatial distribution across two scales (affect and valence) [44, 45]. Such an approach argues that a spatial model provides a conceptual structure for related affective concepts in such a way that allows the self-reporting of affect [44].

A related approach uses affective words to distinguish between related affective states. One of the first measures that took this approach was the Semantic Differential Scale, consisting of a set of 18 bipolar adjective pairs [33]. Each pair is then rated along a 9-point scale. Although heavily used, the measure is extremely cumbersome to use, requiring 18 different measurement ratings for each stimulus and relying on a subject's English reading skills.

Recognising these challenges, there was a move towards pictorial scales, of which the Self-Assessment Manikin (SAM) has become a significant example. SAM consists of three pictorial ranges. For affect (or pleasure), the pictures range "from a smiling, happy figure to a frowning, unhappy figure"; for arousal (or valence), the pictures range "from an excited, wide-eyed figure to a relaxed, sleepy figure"; for dominance, the change is in the size of the figure, "a large figure indicates maximum control in the situation". Under this scale, 'happy' is a pleasurable, slightly arousing and dominant experience; fear is not pleasurable, highly arousing and submissive.

One of the main critiques of the SAM scale is the complexity of administrating it, particularly in terms of explaining the dimensions. Such instruction forms part of the SAM usage protocol. The dominance dimension is conceptually hard to grasp and some have argued that the only intuitive scale is valence (positive vs negative facial expression) [8].

This complexity has resulted in the development of simpler pictorial scales. The 'smileyometer' was developed as a single Likert-scale style set of affective faces [41]. Desmet et al. take an alternative approach, identifying a set of eight distinct emotions and generating cartoon figures that represent those emotions. A questionnaire-based study with 191 participants suggests that their scale can provide robust and reliable assessments of individuals' emotions [9].

Self-reported affect interfaces

Many of the theoretical constructs and scales outlined in the previous section have been developed into digital interfaces so that they can be used in non-laboratory settings without an expert administrating the scale.

The AffectButton system translates a user's cursor position x, y into values representing pleasure, arousal and dominance (PAD). Based on those PAD values, a cartoon facial expression is adapted. This allows a one-click affective report on the three key affective constructs. Based on a variety of studies (including 3 large-scale studies involving 325, 202 and 128 participants respectively), the authors conclude that the interface produces reliable, valid and usable affective results [8]. However, the studies only involved relative young people from the Netherlands.

Rivera-Pelayo et al. take a different approach with their MoodMap App [43]. Based on the two dimensions of Russell's Circumplex Model of Affect [44, 45], the app consists of a spectrum of colour across the two dimensions where users can select their mood based on a position within the colour spectrum. The results of a field study with 71 people across two call centers over four weeks suggest the app could improve work performance and team communication.

Sarzotti had the aim of making mood collection fun and engaging. They developed the Mood TUI – a cube with a different emoticon on each face of the cube [49]. By rotating the cube, the user selects what mood they are in by which face is pointing up when placed on a table. 32 participants took part in a discussion session based around the Mood TUI. While participants were interested in the design, without a evaluation assessing the validity of the data collected it is hard to assess how useful the device would be.

It is notable that none of the interfaces explicitly discuss their applicability to older adults, with the majority of study populations being young adults [8, 9, 15, 17, 19, 20, 29, 43, 49]. Given that older adults have distinct physical and cognitive differences from this population, we cannot assume that these results are transferable to an older population.

There is a clear need for technologies that allow older adults to log their emotions. In developing our prototypes, we focused on designs that would be suitable for older adults to use in their homes over a long period of time, which would enable them to age in place.

3 DEVELOPING THE PAPER PROTOTYPES

Designing for long-term use by Older Adults

Given our design context, our first consideration was choosing the most suitable format of the prototypes.

With aging, people can experience various degrees of decline in their physical and cognitive abilities. This results in various interactional challenges for older adults when operating conventional graphical user interfaces [37, 51]. For example, reduced vision makes it harder to read the screen output and reduced motor skills makes selecting items with a mouse difficult and slower [55]. Several authors also note the difficulties encountered by older adults when interacting with touch screens [12, 34]. The lack of haptic feedback in such interfaces can create perceptual difficulties [57].

Many researchers have therefore proposed exploring Tangible User Interfaces (TUIs) as a more suitable interaction media for older adults which lower the learning curve and are more acceptable in domestic settings [23, 24, 51]. A variety of studies have started to explore how to design tangible technologies for older adults, arguing that they are more appropriate than their GUI-equivalent [24, 37, 51].

TUIs have also been found to increase engagement with mood logging, something which is important to promote ongoing use [49]. Furthermore, a recent systematic review of the last 10 years of HCI health literature, with a detailed analysis of 139 papers, concluded that "HCI ought to be pushing the research front on... novel tangible interfaces" particularly in the context of wellbeing, due to the value of engaging with interfaces outside of virtual or online environments [47].

Our first design decision was therefore to focus on the design of a TUI prototype for logging emotional states.

Selecting the emotion scale

Given the range of types of scales (namely pictorial-based, word-based and continuous scales), we wanted to develop a prototype for each type. This would allow us to explore whether the type of scale impacted the ability of participants to record their emotions using the prototype. It would also allow us to explore whether there were any usability concerns connected to the type of the scale.

Given that we wanted to compare the type of scale, it made sense to select scales based around the same fundamental conceptualisation of affect. We chose scales based around Russell's circumplex of affect as an established scale which also had continuous, word-based and pictorial representations. We selected the circumplex itself, the emotive words from Russell's circumplex and Desmet's pictorial scale [9], based on anthropomorphic cartoons of the emotive words from the circumplex. While none of these scales were exclusively designed for use with older adults, they have been widely used with this population and are accepted to be accurate measures of affect.

Figure 1 shows how the three scales represent the same conceptualisation. Taking the emotion of 'excited', the blue-highlighted quadrant can be taken to represent the emotion 'excited' in the circumplex, it is represented by the word 'Excited' and the picture from Desmet is of an excited person.

This also led us to focus on developing prototypes that could record eight emotions (as this corresponds to the number of emotions expressed in Desmet's pictorial scale). The emotions we are focussed on recording are thus set as: *Happy, Excited, Nervous, Annoyed, Sad, Bored, Calm* and *Relaxed*. These eight emotions provide wide coverage over the range of potential emotions and are a commonly used sub-set of representative emotions [9].

Designing the Paper Prototypes

Our designs were derived from a series of 5 group ideation sessions in which the HCI members of our research team generated and refined a variety of ideas for technologies that could represent the selected scales (the circumplex, emotive words and the pictorial scale from [9]) in a tangible form. The ideation in these sessions was guided by previous work on tangible mood devices (e.g. [43, 49]) while drawing on the researchers' creativity.

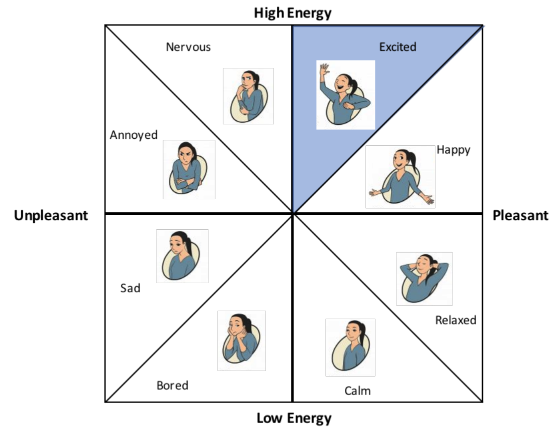

Figure 1: A representation of how the circumplex of affect [44], emotive words from [44] and pictorial scale from [9] are all representations of the same scale.

These ideation sessions resulted in a set of eight potential designs which were tangible representations of the selected scales. All of these designs were constructed in the form of paper-prototypes and other non-functional artefacts.

We presented these designs to our partners from Age UK Exeter and our social and clinical psychologists at a whole-day workshop. During this meeting we discussed their views on the designs, considering their appropriateness for use by older adults in terms of both ease-of-use and ease-of-understanding.

Based on this workshop, we iterated over the prototype designs, resulting in three prototypes that a) had a strong link to an existing scale and b) had a form that we believed would best integrate into a home location, being based on a format that would be familiar (a clock, a picture frame and a dice). At this stage, we also selected the scale that the research team believed would be most suited to that form of tangible interaction.

We pilot tested these designs with two older adults. The feedback from these pilots was used to further refine the prototypes into designs that were suitable for use by older adults, particularly by refining the sizing and materials used in the prototypes. The resulting designs were named the *Emotion Octagon*, the *Emotion Clock* and the *Emotion Board*.

Emotion Octagon

The *Emotion Octagon* took inspiration from the Mood TUI cube developed by Sarzotti [49]. Accepting that this is an engaging way of selecting an emotion, which doesn't require fine-grain motor control, we decided to use a more validated representation of emotion, selecting the pictorial scale in

Desmet et al. [9]. As this scale uses eight different images of people to represent eight different affective states, we had to develop an octagonal representation with each image from the scale on a different face (see Figure 2). A user selects an emotion by placing the picture that represents their emotion facing upwards.

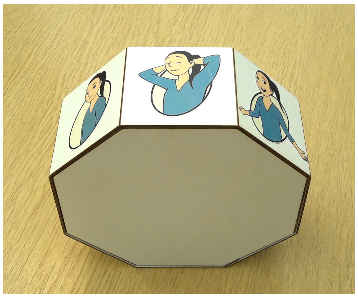

Figure 2: The Emotion Octagon, using the pictorial scale in [9]. Currently showing the 'Relaxed' option selected.

Emotion Clock

The *Emotion Clock* is based on the emotive words positioned around Russell's circumplex [44, 45]. We utilised this concept by taking eight emotive words from the descriptive labels for each of the figures from the pictorial scale from Desmet et al. [9]. These words are arranged around a clock-face in accordance with Russell's affect/valence circumplex [44, 45] (see Figure 3). A user selects an emotion by rotating the clock hand to the word describing the emotion they want to convey.

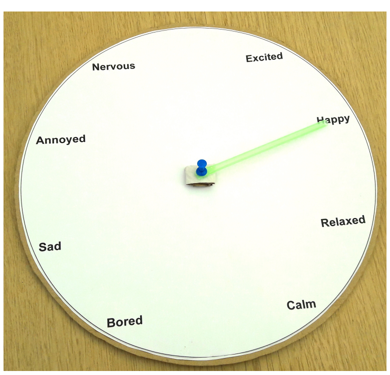

Figure 3: The Emotion Clock, using a subset of the emotive words in [44]. The user has chose the 'Happy' emotion.

Emotion Board

The *Emotion Board* is a tangible representation of Russell's axes [44, 45], using the colour scheme from Rivera et al. [43] (see Figure 4). We added the colour scheme to the original design based on the feedback of Age UK Exeter and our social and clinical psychologists who believed it would make the prototype more engaging.

The axes are labelled *High Energy* to *Low Energy* (top to bottom) and *Feeling Bad* to *Feeling Good* (left to right). A user moves a magnet around to select a position on the axes and thus represent an emotive state.

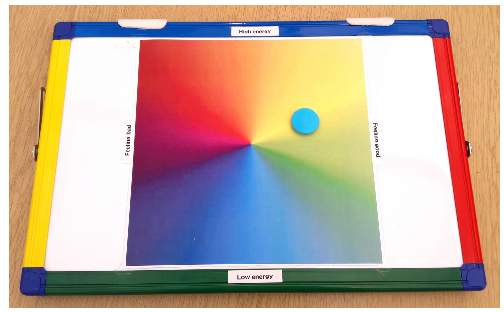

Figure 4: The Emotion Board, based on the Russell axes in [44] using the colour scheme from [43].

4 METHOD

We have two key concerns in exploring the value of these prototypes. The first is whether participants can accurately record their emotional state through the prototype. In doing so, we demonstrate the potential to use TUIs for older adults to record their emotions in a meaningful way.

The second is to capture older adults' attitudes and perceptions towards the three prototypes and to explore their willingness to place something similar in their homes. If the TUIs are capable of recording excellent data but no one is willing to use the devices, we will still be unable to collect affective data over the long-term from older adults.

Our study was designed in accordance with our University's code of ethics. Each of the designs was piloted and was found to induce no discomfort. We allowed participants the right to refuse to use any of the designs, and we made it possible for participants to immediately end their use of a design if they experienced any discomfort. None of the participants opted to do so. We also piloted the study method with two participants, refining our study procedure.

Participants

Participants' ages ranged from 63 to 90 years old (M = 72.64 years, SD = 8.4). All 14 participants had English as their first language. None of the participants had disruptive cognitive or physical difficulties. Participants were recruited through Age UK Milton Keynes or personal contact with the authors.

Procedure

To gather feedback about the designs, we employed a lab-style approach, followed by a short interview. One session took place at a participant's home; the other 13 took place at the Age UK Milton Keynes centre. While this is not a domestic location, it is more familiar than a lab-setting while not requiring participants to allow researchers into their homes. The sessions lasted between 25 and 46 minutes (*mean* = 32 minutes). Each session was one-to-one between the researcher and participant. Our procedure was as follows:

(1) Study Introduction. Sessions began by the researcher explaining that the purpose of the study was to explore new ways of logging emotion and highlighting that no personal emotional experiences would be logged. Informed consent was then collected. At this point, participants were given a brief explanation of the prototypes and how they represent the two dimensions of emotion. The researcher answered any questions the participant had regarding the prototypes.

(2) Prototype Introduction and Use. To ensure coverage across different emotional states, we decided to use standardised emotive vignettes. For this purpose, we gained access to the Affective Norms for English Text (ANET) vignettes which are linked to known Self-Assessment Mannikin (SAM) scores, giving us a known emotion associated with each vignette [6]. These texts have previously been used in studies of emotional interfaces [8]. For each of the eight emotions (Happy; Calm; Nervous; Excited; Sad; Relaxed; Bored and Annoyed), we selected a short vignette with SAM scores corresponding to that emotion.

Unfortunately, part of the procedure for using ANET is to keep the vignettes confidential so we are unable to reproduce them here. However, to illustrate the nature of the vignettes, the examples below were written by the first author:

1) "You receive a phone call telling you that you have won the star prize of a million dollars in the crossword competition you entered last month" [Excited]

2) "You discover that your pet has passed away peacefully in their sleep while you were at work" [Sad]

Participants were provided with the texts in a randomised order. Having read the text, participants were asked to think about the emotion expressed by the text. They would then provide a verbal description of that emotion (which we shall refer to as the *participant description*). In all cases, participants provided a verbal description that was a synonym of one of the eight emotions (e.g. 'nerve wracking' becomes 'Nervous'). The *participant description* allows us to ensure that the emotion logged by the participant through the prototype matches the emotion the participant wanted to log.

Participants were provided with each of the designs in a randomised order; participants were then asked to record the emotion from the vignette through the prototype. The researcher recorded the result for the prototype alongside the time taken by the participant to record the emotion. This timing data is used as a proxy for usability, assessing that none of the prototypes took an unreasonable amount of time to use (either through confusion of how to log an emotion, or difficulty of using the interface).

Participants were also asked to follow a think-aloud protocol and notes were taken throughout.

(3) Wrap Up Interview. We concluded by asking participants to complete a short interview which was audio recorded. Participants were asked about what they thought generally about the idea of recording their emotions, how hard they found each prototype to use, how hard each prototype was to understand and their opinions about having a similar device in their home.

Sessions ended with a short debrief, during which time participants were thanked. Participants were not remunerated for taking part.

5 ANALYSIS

In analysing the data from the study, we have two main concerns. The first is the accuracy of the prototypes – can participants log the emotion they want to log through the prototype devices? The second concern is exploring the participants' views of recording their emotion, how hard they found each prototype to use, how hard each prototype was to understand and their opinions about having a similar device in their home.

Accuracy of the prototypes

The data from each of the prototypes can be analysed in two different ways: categorically and ordinally. Data from each of the prototypes can be treated as categorical data. For each vignette we have 'ground truth'; that is, as they are from a validated set of emotive texts, we know the emotion the vignette should be provoking in our participants. We also have the *participant description*, the emotion the participant believes each vignette expresses. To determine whether the prototypes allow participant's to log the emotion they want to record, we can use Cohen's kappa to compare the emotion recorded through the prototype against a) the expected emotion from the vignette and b) the *participant description*. Cohen's kappa ranges from no agreement (k=0) to complete agreement (k=1) [31].

The problem with treating the data as categorical is that it removes any connection between the different emotions. For example, if a participant records 'Happy' instead of 'Excited', that is a closer match than if they record 'Sad'. An alternative way of conceptualising the data is as two ordinal scales. Each of the prototypes uses a scale based on Russell's circumplex of affect (see Figure 1), therefore each emotion can be represented as a pair of figures ranging from -2 to +2 for both Affect and Valence (see Figure 5).

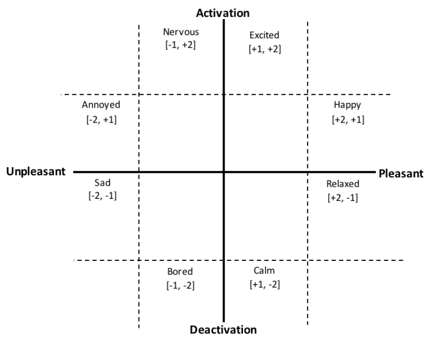

Figure 5: A representation of how the emotions can be given ordinal values on the circumplex of affect.

As an indicator of similarity, it is possible to calculate the Euclidean distance, by calculating the distance between two matrices (the expected emotional values and the actual emotional values) with each matrix being formed of the affect and valence values. The distance reflects the size of dissimilarity between the expected emotions and the recorded emotions; the more dissimilar, the greater the distance between them. The Euclidean distance between two observations is the length of the line between them. The equation below is used to calculate the distance across all samples:

$$D_i = \sqrt{\sum_{j=1}^{n}(A_j - B_j)^2}$$

In both the categorical Cohen's kappa and the ordinal Euclidean distance, we are not interested in the statistical performance *per se*; we are looking for confirmation that the prototypes are allowing participants to log the emotion they wish to record.

Analysing participants' views

The interviews were audio recorded and transcribed. Transcripts were subjected to an inductive thematic analysis [7] in which we explored our participants' views of the prototypes. No codes or themes existed prior to the analysis; they were created through constant comparison of the data and the application of labels to the text.

This qualitative analysis was supported by analysing (with an Anova test) how long it took to use the prototypes.

6 RESULTS

Accuracy of the logged emotions

The importance of using the standard ANET vignettes, alongside the *participant description*, is that they provide baseline data of the emotion associated with the vignette and what the participant wanted to express. This can then be compared against the emotions collected through the three prototypes.

The first stage of this comparison is to examine the results as categorical data. We are comparing the results collected through the prototypes against the expected result based on the ANET vignette scores and the participant described emotions. Table 1 presents the results from calculating Cohen's kappa for each prototype. The results show at least moderate agreement (all Kappas > 0.46 at p<0.001) [27].

When calculating the results, and analysing the interviews, it was clear that participants struggled to differentiate between the 'Relaxed' and 'Calm' vignettes. The italic figures in Table 1 also provide the Kappas for each prototype *excluding* data relating to these two categories, demonstrating increased levels of agreement.

The Kappa results highlight that the Emotion Clock has the most matches between intended emotion and expressed emotion, followed by the Emotion Octagon and the Emotion Board prototypes.

Prototype	Vignette	Participant Description
Emotion Clock	0.62 *(0.82)*	0.74 *(0.82)*
Emotion Octagon	0.5 *(0.63)*	0.63 *(0.66)*
Emotion Board	0.5 *(0.63)*	0.46 *(0.61)*

Table 1: Cohen's kappa values for each prototype. Figures in italics are Cohen's kappa values for each prototype excluding the relaxed/calm data.

Prototype	Vignette Total Distance	Participant Description Total Distance
Emotion Clock	80.7	55.7
Emotion Octagon	106.6	73.2
Emotion Board	122.5	124.5

Table 2: The Euclidean distance for the affect and valence data recorded through each interface compared against the expected data from the vignette and the participant description.

We now examine the results as ordinal data. We calculated the Euclidean distance between the affect/valence values collected through the prototypes and the expected affect/valence from the vignettes. We also calculated the Euclidean distance between the values collected through the prototypes and the participant's description of the vignette. Table 2 shows the Euclidean distances for each of the prototypes. To interpret these figures, it is important to note that there are a total of 112 data points (8 vignettes from 14 participants) on two scales running from -2 to $+2$.

To contextualise the data, we also calculated what the Euclidean distance would be if, for a given interface, all participants were one emotion out (see Figure 5, e.g. the expected emotion was 'Excited' and the participant records 'Happy'). Such a scenario provides a Euclidean distance of 158.4. We also calculated what the Euclidean distance would be if, for a given interface, all participants provided the opposite emotion (e.g. the expected emotion was 'Happy' and the participant records 'Sad'). Such a scenario provides a Euclidean distance of 500.9.

Compared against these contextual calculations, our results in Table 2 show at least moderate agreement between the expected emotion and the recorded emotion. This suggests that the disagreements between expected emotions and recorded emotions noted by the Cohen Kappa results were not large discrepancies (e.g. logging 'Happy' instead of 'Sad') but small (e.g. logging 'Excited' instead of 'Happy').

Consistent with the Kappa results, these results show a clear difference in the accuracy of the prototype responses with the emotions logged through the Emotion Clock being the closest to both the vignette and *participant description* values, the Emotion Octagon being the next closest and the Emotion Board having the least accurate results.

The cross-tabulation presented in Table 3 shows the participants' responses recorded through the prototypes as compared to the expected emotion from the ANET vignette. This data highlights the challenge of categorising emotion in this fashion: Happy/Excited are used almost interchangeably and Relaxed/Calm are difficult to distinguish.

Speed of using the prototypes

The first element of exploring the usability of the prototypes was to establish whether there were any significant differences in the time taken to use any of the prototypes. The mean time for entering an emotion was low: Emotion Clock took 5.93 seconds, Emotion Octagon took 12.41 seconds and Emotion Board took 8.59 seconds.

We ran a two-factor Anova with replication to find whether there was a significant difference in the time taken to record an emotion by prototype ($F=11.02$, $p<0.005$), by vignette ($F=0.75$, $p>0.05$) or by the interaction of both ($F=1.29$, $p>0.05$). This shows a significant difference in the amount of time taken to record an emotion by the prototype.

To establish where the difference is, we ran three paired t-tests comparing the Emotion Clock against the Emotion Board ($t = -2.22$, $p<0.05$), the Emotion Clock against the Emotion Octagon ($t = -5.42$, $p<0.05$) and the Emotion Octagon against the Emotion Board ($t = 2.41$, $p<0.05$). This demonstrates that it was quickest to record an emotion through the Emotion Clock, then the Emotion Board with the Emotion Octagon the slowest.

The next stage in presenting our results is to examine what the interviews with our participants reveal. Our thematic analysis resulted in three broad level themes: a) whether the older adults could see a purpose in using the prototypes to record emotions; b) specific insights into the particular prototype designs; and c) the suitability of the prototype designs for use with older adults.

Perceived need to record emotion

All of our participants could see a purpose in recording their emotions on a regular basis.

Most of our participants (9/14) saw recording their emotion as a mechanism for sharing their feelings over time with other people. Broadly speaking, this was seen in the context of wellbeing either in terms of sharing with family members: *"I think for other family members to be aware of, would be good"* [P4] or with carers: *"If I was living at home and I had a carer coming in, I would be prepared to slide that around somewhere on a day and go 'Yes, I feel a bit blue-esy today' or 'I don't feel so good'... it's a way, perhaps, of expressing something quite complicated without having to go into any great detail"* [P3].

Almost half (6/14) of our participants saw benefits in recording their emotion in terms of being able to self-reflect on their feelings and, if necessary, change their behaviour: *"because sometimes you do feel a little bit down but don't know why. So, I suppose you could, if there was a pattern, you could help"* [P11], *"if you had some mental health issues... if you were depressed, or anxious, or something like that, as part of therapy it might be that you record that on a daily basis... I could see that working"* [P5].

Prototype preferences

When asked to select the prototype they were most likely to use in the future, the participants were fairly evenly spread with 5 participants selecting the Emotion Clock, 4 selecting the Emotion Octagon, 3 selecting the Emotion Board and 2 participants unable to choose between the Emotion Clock and the Emotion Board.

These decisions followed a remarkably consistent pattern. Most (11/14) participants stated that the Emotion Clock was the easiest prototype to use, primarily as the decision-making process was so straightforward. Selecting an emotive word required little interpretation or thought: *"because it did the exact moods, whether you were happy, excited"* [P2]. While this lack of thought created a simple prototype, it was also interpreted as trivialising the process.

The Emotion Octagon created an additional process of interpretation which required more thought: *"[it was] more difficult to understand, because on some of the answers, I couldn't find a picture that really said how I felt"* [P4]. Three of our

	Expected emotion from the ANET vignette								
Emotion recorded in the prototype	**Happy**	**Excited**	**Nervous**	**Annoyed**	**Sad**	**Bored**	**Relaxed**	**Calm**	**Total**
Happy	24	10	0	0	0	3	9	4	50
Excited	13	27	1	1	0	0	1	1	44
Nervous	1	3	20	3	2	1	0	0	30
Annoyed	0	1	7	36	3	1	0	2	50
Sad	0	0	10	1	32	1	0	2	46
Bored	0	0	1	1	3	24	0	11	40
Relaxed	2	1	1	0	0	11	28	12	55
Calm	2	0	2	0	2	1	4	10	21
Total	42	42	42	42	42	42	42	42	336

Table 3: Cross-tabulation of emotions associated with the vignette and the emotion recorded through the prototype for all participants

participants preferred the Emotion Octagon as a compromise between simplicity and reflection: *"you need to be a bit more analytical... you had to think about what it meant"* [P5].

However, the Emotion Board was generally agreed by six participants to require the most interpretation: *"you've got more of a nuance there because you've got a range of mood in between"* [P3], *"because it makes you think about it more. You'll think about your answers more"* [P7].

In terms of engagement, the simplicity of the Emotion Clock made it unengaging. The use of faces on the Emotion Octagon provided a media that people could relate to, that appeared to lead to a greater level of engagement: *"The facial expressions can sometimes mean more to people, in a subtle way, than the actual words"* [P3]. However, five participants found it challenging to interpret the emotion expressed by the faces: *"you can look at faces and see different things. Someone might think that's a happy face, you know?"* [P11].

The most engaging interface for eight of our participants was the Emotion Board, partially due to the flexibility in where to record their emotion but also due to the use of colours: *"the colours actually help convey mood a lot"* [P7], *"is more open if you want to look at colours and that. I always think yellow is a happy one. red can be a bit excitable. I do like green, because it's serene"* [P6]. The emotional connotations of colour are extremely complex, culturally specific and beyond the remit of this paper. However, it is worth noting that these connotations appear to have been individualised and important in terms of engaging our participants.

Suitability for older adults

We have previously discussed how there is some research which indicates that TUI devices are easier for older adults to interact with than GUIs [12, 23, 24, 34, 37, 51, 55, 57]. Building on this, and work which suggests that TUIs provide an engaging way of logging emotions [49], we wanted to explore our participants' thoughts regarding the suitability of the devices for older adults.

The first aspect was tangibility. Half of the participants discussed how the physicality of the prototypes made them easier to operate even with arthritis: *"It's easier to hold for me anyway, and I'm paralysed in this hand... it's arthritis"* [P1].

There was some indication that the participants found the interfaces engaging, that the physicality of the interaction was pleasant: *"I liked physically handling this [the Emotion Octagon]... turning the cube and looking at the faces and then picking the face"* [P12]. Only one of our participants (P5) suggested that a smartphone app would be something they would be more likely to use.

Our last question around suitability was if participants would like to keep the prototype, in which room in their home they would be most likely to place it. The majority of our participants selected public areas of their homes (seven chose the living room, one chose the dining room, one chose the front door) with only one participant choosing a private area (their bedroom). Not only does this indicate the appropriateness of the prototypes, with 10 of our participants wanting to keep the prototypes, it also indicates that our participants were not concerned about other people seeing the prototypes and questioning their purpose.

7 DISCUSSION

Our research questions were focussed around two key concerns. The first is whether participants can accurately reflect their emotional state through the prototype. Our data clearly highlights that all three prototypes allowed participants to accurately log the emotion they wanted to record.

One of the surprising findings from our data is that none of the prototypes are notably more accurate in recording the emotion a participant wants to log. This indicates that any of the prototypes could be used to accurately record emotion.

Our findings also demonstrate that our participants saw value in the devices if a suitable intervention can then be provided. Such a position is common in self-tracking systems aimed at supporting behaviour change [10, 17]. There was a clear difference in which device would enable them to log constrained or open emotion options. Whether they preferred constrained or open options was dependent on the perceived purpose of the device.

Participants who preferred the constrained Emotion Clock tended to see the need of the device as sharing a general report of their affective state with others (be that family or carers). The expectation is that the family/carers would further explore the emotional state of the older adult and work with them to improve their wellbeing. Those participants who preferred the more open-ended Emotion Board, saw the device as a mechanism for self-reflection, using the act of logging as a way of self-checking their emotions and potentially enacting behaviour change as a result. Both of these perceived needs are important, given the clear link between successfully ageing, physical health and wellbeing [53].

In both cases, the level of granularity of emotion is relatively large; knowing that someone is relaxed rather than calm is less significant than whether someone is happy or sad. Given the context, we would argue that the prototypes provide sufficiently detailed data that could be used to support older adults wellbeing. Such a finding also suggests that there is a need for a clear use case associated with the design of an interactive device to log emotion; either combining the ability to report constrained emotions while leaving open the ability to reflect, or having separate devices.

For both use cases, there is a need to generate a historical record. For those interested in sharing data, this can simply chart the emotions recorded over time. However, for those interested in self-reflection, research in self-tracking has highlighted that in addition to the benefits of reflecting at the moment of collection, there are further benefits to wellbeing in reflecting on the data at a later point [13, 30, 56]. This is an area of research that needs further work.

Our second research question was whether older adults could use the three prototypes to record their emotions. Our timing data shows that our participants could record emotions at a reasonable speed through all three prototypes, particularly when compared to the amount of time needed to complete a diary entry or a questionnaire.

Our results also highlight that the tangible nature of the devices was useful, particularly for those older adults who have arthritis or other musculoskeletal difficulties. Given that arthritis is a common condition, particularly in later life [4], and that musculoskeletal difficulties can limit the ability of an individual to control a GUI [46], it appears as though a tangible device is much more suitable for use by older adults.

In terms of engagement, all of our participants were interested and excited by the tangible prototypes. A recent literature review has established that the real-world uptake and engagement of self-help apps varies dramatically but is relatively low, particularly over the longer term [14]. As such, we would argue that focussing on using a tangible approach for long-term engagement with the use of the self-tracking technology is a route for further work.

8 LIMITATIONS AND FUTURE WORK

It is important to note a number of limitations with our approach. In terms of the prototype designs, we did not compare all of the potential designs in terms of the combinations of the scale selected and the interface type. While we have demonstrated the potential for TUIs to acts as tools for older adults to log their emotion, we do not offer our specific devices as the most effective designs.

For example, as three of our participants noted, the way all three prototypes are configured means that it is not possible to record multiple emotions. These shortcomings are inherent in the standardised scales we based our prototypes on and need to be considered when translating the prototypes into functional devices.

Similarly, in basing the prototypes on standardised scales, we constrained the range of emotions that could be logged – in the current designs, it is hard to express emotions such as 'thoughtful', 'suspicious' or 'horror'. Further work is needed to explore whether a wider range of emotions are needed in the context of supporting wellbeing for older adults.

Beyond this, there is a broader question around the use of TUIs for logging emotions. Our work demonstrates that tangible interfaces can be used for selecting emotions with the same degree of accuracy as paper-based interactions also based on selection. It is interesting to consider what tangibles could offer beyond this if we move away from standard scales of emotion and focus on developing tangible expressions of emotion. While not the aim of this paper, we offer this suggestion as a direction of further work

9 CONCLUSION

In this paper we have contributed an empirical investigation into the suitability of using TUIs based on standardised scales of emotion for older adults to log emotions. We conclude that some of our prototypes are sufficiently accurate in collecting emotional data from older adults. We further demonstrate that the tangibility of the prototypes is engaging for older adults and that our study population could foresee practical uses of the prototypes, particularly as tools for sharing their emotional data and as a mechanism for self-reflection.

This study provides foundational support for a range of discrete and continuous tangible emotion self-logging devices for older adults. In future work we plan on exploring whether implementations of our prototypes can collect meaningful data in the long-term in an individual's home and explore whether such devices can support the wellbeing of older adults as they age in place.

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