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HealthClockface: Design of Glanceable Health Data Visualization for Smartwatches

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Remote measurement technologies (RMTs) hold promises for health tracking, yet current health data visualizations in RMTs primarily target data-savvy experts, posing challenges for those with limited expertise. Although researchers have explored creative visualization methods, they often fall short in aiding data comprehension and neglect the needs of individuals and informal caregivers. This paper introduces HealthClockface, a smartwatch clockface that offers a glanceable visualization of health data using abstract and dynamic visuals generated by chaotic attractors. Designed for non-expert users, the system translates real-time inputs into ambient, glanceable feedback that supports awareness of one's health. The system was developed through an iterative, user-centered design process and implemented on commercial hardware. User feedback highlighted the aesthetic appeal and engagement of the visualizations, although some users expressed concerns about the interpretability and clarity of the abstract visuals, particularly when more detailed information was needed. This paper explores the potential of using ambient, artistic visualizations for health monitoring and highlights the challenges related to clarity and interpretability, offering insights for future research and design in remote measurement technologies.

Keywords: Remote Measurement Technologies, Health Monitoring, Glanceable Visualizations, Ambient Information

1 Introduction

Remote Measurement Technologies (RMTs), such as smartwatches and fitness trackers, have become widely used for everyday health monitoring (Polhemus et al., 2022). These devices help people collect, store, and transmit a broad range of health-related data during their daily activities (Polhemus et al., 2022), such as physical activity, heart rate, and sleep quality (Simblett et al., 2018), through remote interfaces (Walsh et al., 2022). Well-designed data visualizations can enhance user engagement with RMTs by supporting intuitive understanding and meaningful interaction with health data (Polhemus et al., 2022; Lu et al., 2025). However, current health data visualizations used in RMTs are often

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presented in conventional forms, such as bar charts, pie charts, scatterplots, and tables (O'Connor et al., 2020; Blascheck et al., 2018), primarily targeting data-savvy experts, such as data analysts and health researchers (Lee et al., 2020). These conventional forms pose challenges for broader audiences who often lack the necessary expertise to interpret complex health data (Roth et al., 2015). A recent review by Lu et al. (2025) highlights that visualization design in health tracking remains underdeveloped, with many systems lacking meaningful or engaging data representations.

Additionally, the health data visualizations are typically confined to application interfaces, requiring deliberate action to open and interpret. This limits casual or frequent checking of health information in the flow of daily life. In such contexts, glanceability, which is the ability to obtain relevant information with minimal cognitive effort and attention, is an important yet underexplored quality in health data visualization (While et al., 2024). A glanceable visualization allows users to retrieve health information quickly and unobtrusively (Blascheck et al., 2021). These visualizations fall under the broader category of ambient information systems, which provide subtle, peripheral awareness of information without requiring focused attention (Moreira et al., 2024). This is especially relevant for wearable devices like smartwatches, which are often checked briefly throughout the day (Blascheck et al., 2018). Although many commercial smartwatches already offer quick health feedback (e.g., Apple Watch complications and Garmin activity rings), these visualizations are typically quantitative and goal-oriented, presenting data icons with text, progress bars, rings, or numerical summaries (Islam et al., 2020). While effective for performance tracking, they often lack expressive or affective qualities and are mainly designed for data-literate users. As such, there remains a need for further design of novel visualization approaches that can efficiently present health data to a wider audience. These solutions should also integrate with 'always-on' display devices to enable seamless user engagement with their health information.

In this paper, we introduce HealthClockface, a smartwatch clockface that offers a glanceable 'always-on' health data (heart rate and activity level) visualization using abstract and dynamic visuals generated by chaotic attractors (Peitgen et al., 1992). It is designed for non-expert users, including people who track their own health or support others. HealthClockface transforms real-time physiological data into aesthetically engaging patterns on a smartwatch screen, allowing users to understand their health state at a glance.

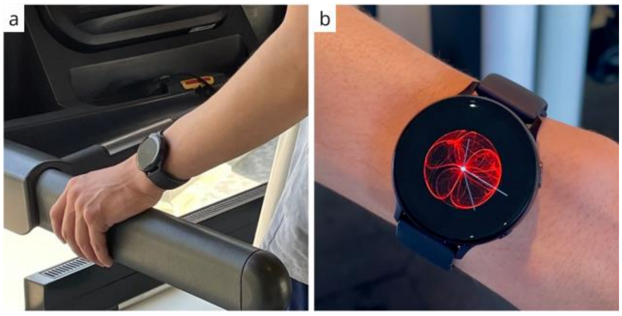

Figure 1. HealthClockface is a live clockface on the Samsung smartwatch, visualizing heart rate and activity. The user (a) is working out; he activates the live clockface by raising his arm and then takes a closer look (b).

HealthClockface was implemented on a Samsung smartwatch to help users keep track of their vital signs and fitness goals, as shown in Figure 1. HealthClockface was evaluated in a video walkthrough evaluation with 57 participants, including individuals with cardiovascular conditions and informal caregivers, to assess its usability and appeal. The results show that HealthClockface was perceived by the participants as aesthetically pleasing, engaging, and helpful for staying aware of their health. Some also raised concerns about its practicality in situations where more precise information is needed.

This work contributes: (1) HealthClockface, a smartwatch glanceable visualization using abstract, dynamic visuals to provide ambient health data feedback for non-expert users; (2) a practical implementation on commercial smartwatches, demonstrating feasibility and seamless integration into daily routines; and (3) findings from the iterative user-centered evaluation, showing that such visualizations can enhance awareness of personal health, engagement, and reflection in daily health tracking.

2 Related Work

Our work draws from research in health data visualization, glanceable visualizations on micro displays, and ambient information displays.

2.1 Health Data Visualization

The visualization of personal health data plays a critical role in RMTs and personal informatics systems. Prior research shows that when visualizations are easy to interpret and visually intuitive, they can enhance user engagement, encourage self-management, and support long-term health behavior change (Simblett et al., 2024). As a result, RMT platforms, including mobile health applications (mHealth), commonly incorporate various forms of data visualization to make physiological and behavioral information more accessible to users (Chan et al., 2025). However, most of these platforms rely on conventional graphical formats such as bar charts, line graphs, sparklines, and progress indicators (Chan et al., 2025), especially on small screens such as smartphones and wearables (Kim, 2022). Furthermore, prior work has noted that users without technical or clinical training may struggle to understand such representations, which can reduce engagement over time (Cajamarca et al., 2023).

In response, researchers have explored more expressive alternatives that aim to simplify interpretation and enhance emotional resonance. Early examples include metaphor-driven and playful visualizations, such as metaphor-driven or playful designs, e.g., UbiFit Garden (Consolvo et al., 2008), and Fish’n’Steps (Lin et al., 2006). While these systems help promote specific health behaviors, they provide limited opportunities for users to interpret or analyze the underlying data (Meyer et al.,2016). Other systems, such as YourWellness (Doyle et al., 2014), simplified visualizations to appeal to a broad user base but remained focused on general well-being, with limited customization for diverse physiological signals.

Recent studies suggest that alternative visualization approaches that are more visually expressive and metaphorical may better support accessibility and sustained use. For example, Simblett et al. (2024) found that individuals managing chronic conditions preferred graphical, image-rich displays that use color, icons, and clear metaphors over clinical or technical visuals. Survey studies further show that users value visualizations not just for monitoring but also for fun and curiosity, indicating a desire for more playful, aesthetically engaging forms of feedback (Alshehhi et al., 2023). Our work builds on this direction by designing visualizations that are visually engaging, easily interpretable, and seamlessly integrated into daily routines through wearable technologies.

2.2 Glanceable Visualizations on Micro Displays

Glanceable visualizations are concise representations designed for rapid insight during brief interactions (Blascheck et al., 2021). They are especially important on devices with small displays, like smartwatches, which users check in very short bursts (Blascheck et al., 2018). To accommodate this usage pattern, most existing wearable health interfaces use static, minimalist designs, with fitness trackers typically displaying heart rate and steps as plain text or simple icons (Cadmus-Bertram, 2017; Grioui & Blascheck, 2023). When visualizations are included, they remain very basic. For example, Neshati et al. (2019) condense line graphs into compact, glanceable formats for smartwatches, yet still rely on the conventional line-chart metaphor. Symbolic or abstract graphics are virtually absent from health watch faces, and existing animations tend to be decorative rather than data-driven (Islam et al., 2020). To our knowledge, prior systems have not explored animated, abstract visualizations for glanceable health feedback.

2.3 Ambient Information Displays

Ambient information displays present data in subtle, often artistic ways that can be perceived in the periphery of attention without requiring focused interaction (Pousman & Stasko, 2006). These displays are typically components of broader ambient information systems, designed to seamlessly integrate into everyday environments while conveying meaningful information in a low-disruption manner. These systems include ambient, glanceable, and incidental displays, each offering different approaches to peripheral information delivery (Moreira et al., 2024). In this work, we focus specifically on glanceable displays, visualizations that can be interpreted quickly with minimal cognitive effort. Previous work has explored this through metaphorical and decorative forms, such as Breakaway sculpture, a kinetic sculpture that slouches subtly over time as a user sits, reminding them to take breaks (Jafarinaimi et al., 2005), or UbiFit Garden, which visualizes physical activity as blooming flowers on a phone wallpaper to encourage regular physical activity (Consolvo et al., 2008). These systems prioritize emotional engagement and gentle self-reflection over precise data interpretation. Shelton and Nesbitt describe such approaches as “aesthetic awareness displays”, visualizations that abstract data into pleasing forms to support ambient awareness (Shelton & Nesbitt, 2016). While ambient displays have primarily been explored in spatial or decorative contexts, their use in wearable interfaces remains underexplored.

3 Design and Implementation

The design of HealthClockface was informed by prior research on user needs in health data visualization (Lu & Hu, 2024) and the specific challenges of presenting data in mHealth applications (Alshehhi et al., 2023). Our aim was to create a glanceable and aesthetically engaging visualization that seamlessly integrates into users’ daily routines. To achieve this, we emphasized the balance between visual appeal and interpretability, relying on simple, intuitive elements rather than complex metaphors. By embedding the visualization within the context of a smartwatch interface, we sought to enable unobtrusive, routine interaction with health information.

3.1 Design Inspiration: Art in Chaos

To support both glanceability and ambient awareness, we explored alternatives to traditional chart-based representations. Generative art, known for its ambient and expressive qualities, offered a promising direction. We were particularly inspired by chaotic attractors (Peitgen et al., 1992), mathematical systems that produce intricate, evolving patterns from simple rules. Their dynamic nature made them well-suited for subtle, ambient displays that unfold over time. Unlike static or random abstract visuals, chaotic attractors are conceptually linked to the natural dynamics of human physiological systems, such as heart rhythms and breathing cycles (Biswas et al., 2018). Chaos theory, as described by Peitgen and Richter (1986), shows how complexity can arise from simplicity, offering both computational elegance and visual richness. Rather than treating these patterns purely as artistic flourishes, we used them as data-driven encodings that could subtly signal changes in health states, aiming to balance visual appeal with informational clarity.

3.2 Design Exploration and Initial Concept

In our initial design exploration, we investigated whether abstract generative patterns could convey meaningful health information in a way that supports glanceable perception. Inspired by HackerPoet's (2019) work on recursive chaotic equations, we used a pair of recursive equations to generate dynamic point-based visuals. Health status was used as a parameter to modulate the complexity and form of these patterns. Our initial mapping scheme associated distinct health states, excellent, good, and poor, with corresponding visual variations produced by the same underlying equations at different time points *t*. An illustrative example is shown in Figure 2, where a specific pair of chaotic equations (Equations 1, 2) generates a progression of visual forms. When health is rated as excellent, the pattern appears complete and well-defined. As health deteriorates, from good to poor, visual representation becomes increasingly sparse and abstract. This reduction in detail was intended to serve as a subtle yet glanceable indicator of health decline.

$$x_t = -x^2 - t^2 + xt - yt - x \tag{1}$$

$$y_t = -x^2 + t^2 + xt - x - y \tag{2}$$

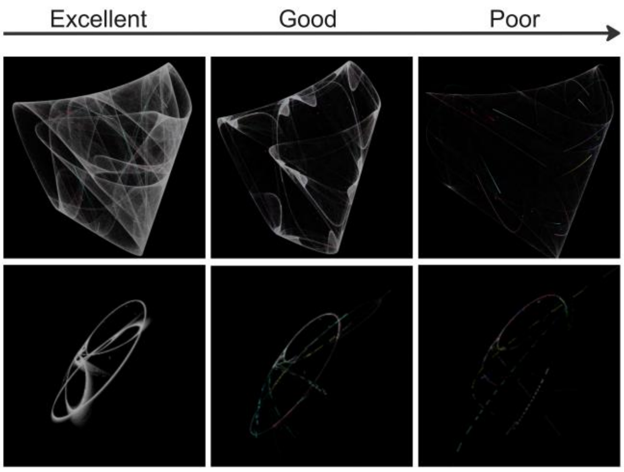

Figure 2. Example visualization of health states transition from 'Excellent' to 'Good' to 'Poor' in the first iteration.

3.2.1 User Study

We conducted a user study to assess whether users can comprehend the design and evaluate its visual appeal, focusing on *Comprehensibility* and *Attractiveness*. *Comprehensibility* refers to the degree to which users can accurately understand and interpret the health states conveyed by the visualization. *Attractiveness* measures how visually appealing and acceptable users find the design of the health data presentation.

The user study involved 12 participants (mean age 30.8 ± 8.99), all of whom regularly tracked health data using at least one RMT, either for themselves or for someone they cared for. To examine *Comprehensibility,* participants were shown four groups of visuals. Each group was generated by the same set of recursive equations and consisted of three visuals, each representing one of the health statuses: excellent, good, and poor. The order of the visuals within each group was randomized. Participants were tasked with matching each visual to one of the three health statuses. Afterward, participants were informed of the intended health status and shown a video demonstrating the visual transition process. To examine *Attractiveness*, participants then completed a survey including basic demographic information, the AttrakDiff2 questionnaire (Hassenzahl et al., 2003), and open-ended feedback. The AttrakDiff2 questionnaire, based on a 7-point Likert scale ranging from -3 to 3, assessed *Attractiveness* using semantic differential scale items. High scores indicated positive experiences, evaluating overall attractiveness from four perspectives: pragmatic quality, hedonic quality identity, hedonic quality stimulus, and attractiveness.

3.2.2 Results

Regarding *Comprehensibility*, Participants averaged 6.5 correct answers (SD = 2.09) out of the visuals presented, indicating low comprehensibility. Many experienced confusion. Even when they answered correctly, it was often based on guessing or comparing with previous visuals. Some associated visuals with unrelated concepts, emphasizing the need to avoid misleading patterns and provide clearer indicators. Relying solely on a single mapping of health status and pattern complexity is insufficient. Regarding *Attractiveness*, the visualization was generally perceived as visually appealing, with an overall mean score (M) = 1.51 on the AttrakDiff2 questionnaire. Within the hedonic qualities dimensions, the hedonic quality stimulus achieved the highest mean score (M = 2.29), indicating strong visual appeal and innovativeness. High ratings for word pairs such as “Conservative - Innovative” (M = 2.76) and “Conventional - Inventional” (M = 2.56) suggest that the participants found HealthClockface to be both stylish and innovative. The hedonic quality identity sub-dimension received a mean score of 1.51, reflecting positive emotional engagement from participants. Furthermore, the word pair “Tacky - stylish” received a score of M = 2.90, indicating a particularly favorable evaluation of the style of the visualization. The pragmatic quality score (M = 0.35) was lower than the hedonic qualities but remained in the positive range. This lower score may be attributed to HealthClockface being in the concept proofing and development stage rather than a finalized product. However, some participants perceived certain aspects of the system as complex or difficult to use, as evidenced by negative scores on word pairs such as “Unruly - manageable,” “Complicated - simple,” and “Unpredictable - predictable” within the pragmatic quality category.

Overall, the results demonstrate user favor for HealthClockface for its attractiveness. However, the low comprehension scores point to a key weakness in its current design: the visuals are attractive but not easily interpretable. To function effectively as a glanceable health tool, the system requires clearer visual mappings that better communicate health status at a glance.

3.3 Final Design and Implementation

The second design iteration focuses on improving the glanceability of the visualization by remapping visual encodings to health data in a way that is quickly interpretable with minimal cognitive effort. We further integrated HealthClockface with real-time health data and applied it to the existing RMT.

3.3.1 Pattern Generation with Chaotic Attractors

To enhance visual clarity and distinctiveness at a glance, we adopted a different approach to pattern generation using a class of recursive equations known as chaotic attractors. These attractors produce visually complex yet stable fractal structures that can be consistently controlled through parameter manipulation (Peitgen et al., 1992). The advantage of using chaotic attractors is that they not only produce beautiful, abstract patterns but can also be finely controlled by adjusting certain parameters. The Peter de Jong Attractor is an example of a chaotic attractor, an iterative system governed by four parameters: a, b, c, and d (Hamdi & Hassen, 2017). The attractor is defined by the equations:

$$x_{n+1} = \sin(a \cdot y_n) - \cos(b \cdot x_n) \tag{3}$$

$$y_{n+1} = \sin(c \cdot x_n) - \cos(d \cdot y_n) \tag{4}$$

By iteratively calculating the coordinates using these equations, a set of coordinates is obtained, which can then be plotted in a two-dimensional space. The resulting patterns generated by the attractor can be varied by adjusting the values of constants a, b, c, and d. Each unique pattern is specific to the particular combination of parameter values chosen (Figure 3).

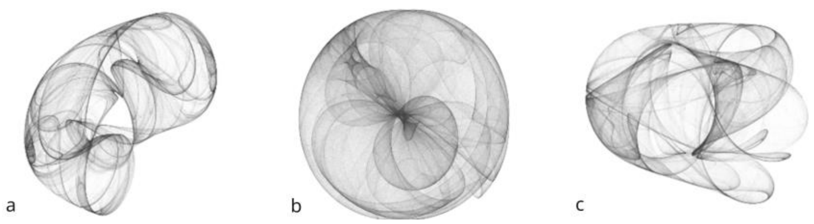

Figure 3. Example visuals generated by the Peter de Jong Attractor using different parameter values: (a) a = 2.0, b = -2.3, c = 2.4, d = -2.1; (b) a = 2.0, b = -2.0, c = 2.1, d = -0.7; (c) a = 2.0, b = -1.1, c = -0.6, d = -2.4.

3.3.2 Parameters Mapping

Two parameters were used to map with health data for visualization: pattern color and visualization motion speed. These properties were chosen because color (hue) and motion speed are recognized preattentively, enabling users to perceive changes in health state with minimal cognitive effort. Prior work shows that hue can elicit instantaneous visual “pop-out” responses and that motion velocity functions as a salient cue in dynamic visual environments (Healey et al., 1996; Cybulski, 2024).

Specifically, we use color temperature that universally evokes associations with hot and cold sensations (Ziat et al., 2016) to present heart rate. In HealthClockface, the visual patterns transition from cooler to warmer colors, representing different ranges of heart rate from low to high (Figure 4). This intuitive color gradient is designed to give users an at-a-glance view of their heart rate status. For heart rates exceeding 160 beats per minute (bpm), HealthClockface employs random behavior dots as a representation of disorder, aiming to draw attention to the potential danger associated with high heart rates, serving as a visual alert for users. The visualization motion speed reflects activity intensity. In a sedentary state, such as sitting, the visualization progresses at a slower speed, gradually building up the patterns over time. During walking, the speed increases, resulting in a faster progression of the patterns. When a user performs a high-intensity activity, like running, the visualization speed reaches its maximum, facilitating nearly instantaneous generation of the patterns. This dynamic speed variation aims to give users an immediate sense of their activity level.

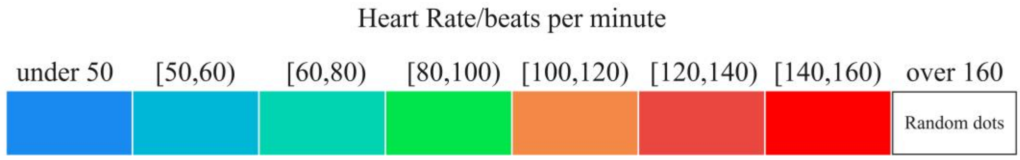

Figure 4. Mapping details of heart rate values and corresponding pattern colors.

Under normal circumstances, heart rate and activity intensity exhibit a direct linear relationship (Wiles et al., 2008). For example, higher heart rates are associated with higher-intensity activities. In this situation, the visual patterns displayed on the screen would exhibit warmer colors (e.g., red) and faster progression speeds. This alignment allows users to intuitively perceive the correspondence between the color representation and the speed of visualization, providing a clear indication of their current level of activity. However, if a conflict arises between heart rate data and activity intensity, like a warmer color displayed with low speed, it signals that something may not be as expected or optimal. This discrepancy alerts users to potential irregularities in their health or exercise performance.

3.3.3 Implementation

HealthClockface was implemented on a smartwatch (Samsung Galaxy Watch Active 2), which features multi-sensors to monitor real-time heart rate and activity level. These health data are collected through the Human Activity Monitor API (Tizen, 2023), processed, and visualized directly on the watch (Figure 5). The smartwatch has a 44mm diameter display with a 360×360-pixel resolution and uses Tizen OS 5.5.0.2 as the operating system. Tizen Studio was used to create a custom watch face. Activity is tracked using pedometer data, categorized as sitting, walking, or running. Instead of fixed data intervals, the system sets up callback functions that are triggered whenever new heart rate or movement data becomes available. HealthClockface was deployed as a watch face application using JavaScript and HTML5 in Tizen Studio. HTML5 canvas has been used to render the watch layout and content. Additionally, the application sets up an event listener to handle visibility changes and ensure that the screen updates immediately when the device wakes up or the screen becomes visible. A user-friendly feature was implemented, allowing HealthClockface to display when the user raises their wrist or taps the screen of the smartwatch.

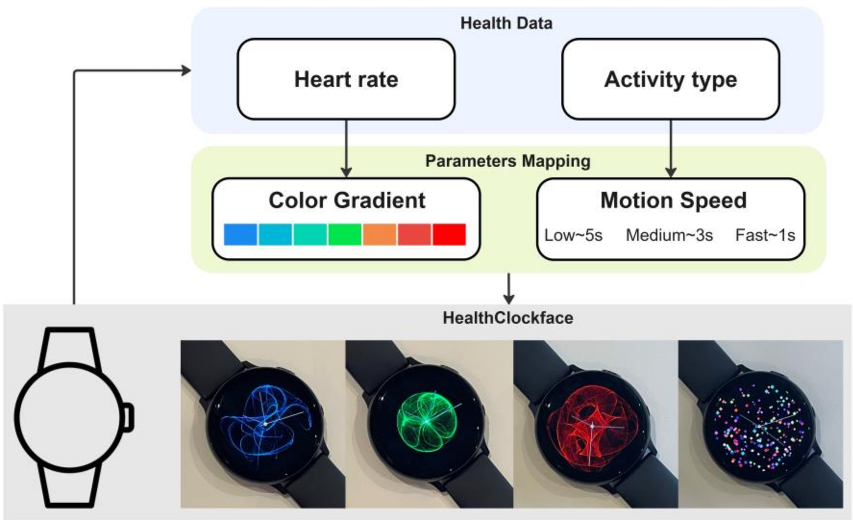

Figure 5. The workflow of HealthClockface.

In the final implementation, we selected the Peter de Jong Attractor and the Pickover Attractor as the initial attractors for their unique and visually appealing chaotic behavior (Sprott, 1998). A set of predefined parameters has been implemented to ensure consistent quality visual outputs. Heart rate values (initially set to 0) are mapped to a color gradient from cool blue (low HR) to warm red (high HR) using a heartRateRanges array. The minimum HR is represented by a cool-tone blue color, and the maximum HR is represented by a hot-tone red color. For HR above 160 bpm, randomly generated dots signal a potential health risk. Visualization motion speed reflects activity intensity, controlled by a "movementStatus" variable linked to animation speed ("timeInterval") for not moving, walking, and running states. The canvas background is set to black to enhance contrast.

4 User study

We conducted a video walkthrough evaluation to explore how non-expert user, who manage their own health or support someone else's, understand and evaluate HealthClockface. Ethical approval was obtained from the university's ethical review board.

4.1 Participants

Participants were recruited via Prolific (https://www.prolific.co) using self-selection and pre-screening filters. Eligibility criteria included being 18 years or older, fluent in English, and having experience using digital tools to monitor the health of their own or someone else's.

The final dataset included 57 participants, divided into two groups: Group P and Group C. Group P consisted of 26 participants (P1-P26) who reported having a cardiovascular condition and used RMTs to monitor their health. Among them, 76.9% (n = 20) identified as male and 23.1% (n = 6) as female. Most participants (53.8%) were aged 45 or older. Group C consisted of 31 informal caregivers (C1-C31) who provided part-time, unpaid care for someone with a chronic health condition. They supported individuals with a range of conditions, including cardiovascular disease, dementia, autism, cancer, and mobility-related challenges.

4.2 Procedure

We developed two tailored surveys: one for participants managing their own health (Group P) and another for caregivers (Group C). Both surveys shared the same core structure and content but were adapted to reflect the perspective of each group. The survey was administered using Microsoft Forms, and responses were collected anonymously. Participants were informed that the survey would take approximately 20 minutes to complete.

At the start, participants were introduced to HealthClockface as a smartwatch-based visualization tool and asked to reflect on its use in daily life.

The study consisted of four main parts. Firstly, participants completed questions related to their demographic information, health-related experiences, and health monitoring practices. Secondly, participants were introduced to HealthClockface, through a short description and a 1-minute, 20-second walkthrough video demonstrating everyday usage scenarios. They were asked to reflect on how they might use the tool in their daily lives. Thirdly, after viewing the video, participants completed the AttrakDiff Mini questionnaire (Hassenzahl et al., 2003), which measures pragmatic quality, hedonic quality, and overall attractiveness. This shortened 10-item version was selected to reduce response burden, given the limited interaction with the system. Participants also answered a set of open-ended questions about their likelihood of using HealthClockface in the future and any final comments they wished to share.

Lastly, participants were presented with two alternative smartwatch visualizations, a numerical display and a graphical display, alongside HealthClockface (Figure 6). They were asked to describe the strengths and weaknesses of each design, particularly in terms of comprehensibility, usefulness, and visual appeal.

Figure 6. A. HealthClockface; B. Numerical background; C. Graphical background.

4.3 Results

4.3.1 AttrakDiff Survey

As shown in Figure 7, mean scores across all three dimensions are above the scale average. To examine whether participants' roles might influence perception, we looked at responses by participant type. Attractiveness emerged as the highest-rated dimension, with Group P giving it a mean score of 2.15 and Group C rating it at 1.76. This suggests that the visual and interactive qualities of HealthClockface resonated well, particularly with users who envisioned applying it to their own routines.

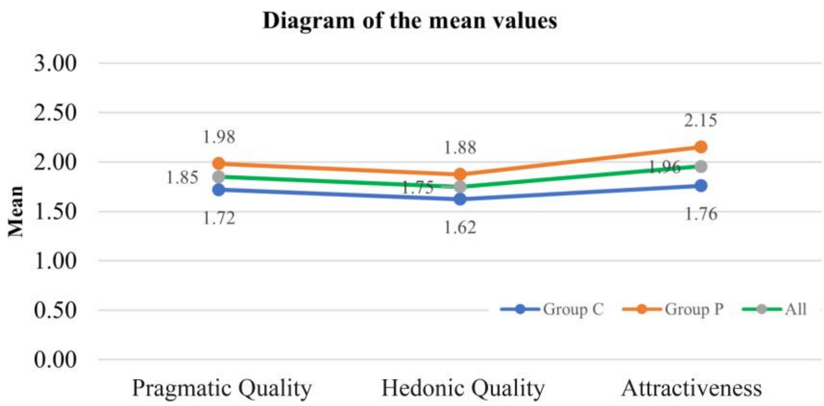

Figure 7. Mean values of each dimension: Pragmatic Quality, Hedonic Quality, and Attractiveness. The results were evaluated using a 7-point semantic differential scale, where responses ranged from -3 to +3. For analysis, the responses were assigned corresponding values of -3, -2, -1, 0, 1, 2, and 3.

Pragmatic qualities, reflecting perceived usability and functionality, were rated higher than hedonic qualities for both groups. Still, both pragmatic and hedonic dimensions were rated above the neutral midpoint of the scale. Notably, Group P consistently rated the system more favorably than Group C across all three dimensions, suggesting a more positive response from those actively managing their own health. Hedonic quality received the lowest scores (M = 1.75 for Group P and M = 1.72 for Group

C), indicating slightly lower perceived novelty or stimulation. The overall profile suggests that HealthClockface is seen as functional, attractive, and suitable for everyday use, especially by Group P.

These findings are further supported by the word-pair analysis (Figure 8), which revealed generally positive associations. Attributes such as “Simple,” “Practical,” “Clearly Structured,” and “Premium” were rated favorably by both groups. However, participants rated the system more negatively on attributes like “Tacky” and “Dull.” Interestingly, while the term “Premium” scored highly, qualitative responses revealed that some participants perceived the system as potentially expensive, which negatively impacted their willingness to use the system in the future.

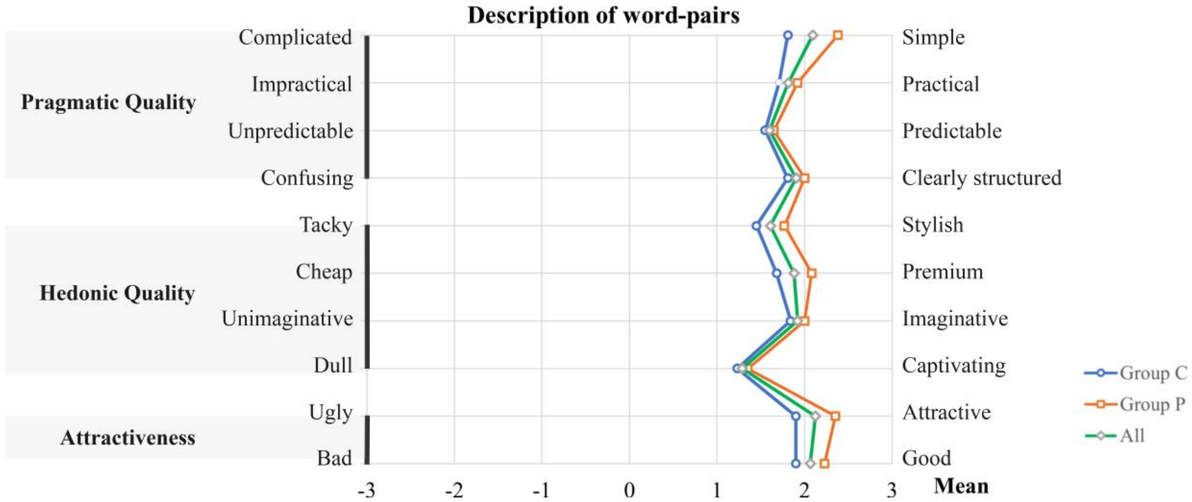

Figure 8. Results of the AttrakDiff Mini questionnaire. Pragmatic Quality, Hedonic Quality, and Attractiveness.

4.3.2 Impressions and Comprehensibility of HealthClockface.

Open-ended responses provided valuable context to the quantitative ratings. Participants described HealthClockface as “easy to access,” “convenient,” and “user-friendly,” emphasizing its practical value. Many appreciated its seamless integration into daily routines, describing it as a “nonclinical” way to check in on health “like part of a routine without being disrupted” (P2). Several participants noted that it could offer reassurance, particularly when monitoring the health of a loved one.

However, comprehensibility fvaried. Though 78.9% (45) appreciated the design’s aesthetics, some reported initial uncertainty in interpreting the visuals. C3 described the clockface as “confusing,” and C15 remarked, “The design looks stylish, but not sure how to read the heart rate.” These comments expose ambiguity in how abstract patterns map to specific metrics. Several participants suggested that a brief explanation or legend would clarify the meaning: “I like how it looks, but I wouldn’t know if it’s good or bad unless someone told me” (P16).

Participants praised the color gradients representing heart rate as both informative and visually appealing. However, some desired more detailed feedback (e.g., numeric overlays) or additional metrics such as oxygen saturation. A few raised concerns about information overload or over-reliance; C4 mentioned that constant visual changes “could heighten anxiety about a family member’s condition.”

4.3.3 Future Use: Motivations, Conditions, and Concerns

Most participants (approximately 75%) expressed openness to using HealthClockface, citing its visual appeal, motivational quality, and potential to support everyday health awareness. For example, one participant described it as “a motivating factor” (P24), and another said it “could help with ongoing health management” (P14). Participants appreciated that the visuals were easy to spot and interpret at a glance, a quality several found especially helpful during busy routines. Many also highlighted the convenience of having the visualization directly on the watch face, eliminating the need for extra steps or switching apps.

However, future adoption was seen as conditional. Factors such as device cost, personalization options (e.g., design styles, color schemes), and the perceived accuracy of the visualizations influenced participants’ likelihood of future use. P2 explained, “I know my body; I feel that I would be aware of any issues”, while another expressed a preference for more conventional visuals like “pictures of a heart” (P6). Some participants, particularly those in caregiving roles, emphasized the importance of automation and alerts. For instance, C11 shared, “I would prefer that the app notified me if there was anything concerning or irregular rather than having to check it frequently”. Others expressed interest in expanding the scope of health indicators, such as integrating oxygen saturation data (e.g., C11, C18), suggesting that the tool could become more valuable if tailored to specific health management needs. A few raised concerns that constant monitoring might introduce stress or over-sensitization to health issues, especially in cases of false alarms. C9 remarked that it might “increase anxiety rather than alleviate it,” highlighting the importance of balancing informative feedback with emotional reassurance.

4.3.4 Envisioned Applications Beyond the Watch

Over 80% of participants saw the broader potential for HealthClockface across devices. Mobile phones and tablets were the most suggested alternatives, often described as lock screens or dynamic wallpapers. C20 imagined it appearing in “the information bar of a laptop”, while others mentioned smart mirrors, in-car dashboards, and even fitness machines as suitable contexts, particularly among participants who don’t regularly wear smartwatches. One caregiver noted, “I only wear a watch sometimes,” preferring it synced across devices (C26). More novel ideas also emerged. One participant proposed its use in augmented reality glasses (P7), while others envisioned integration into household objects like smart keyholders or digital photo frames.

4.3.5 Different Health Visualizations for Smartwatch Use

Participants were shown three smartwatch screen-based visualizations and asked to discuss their preferences, noting the strengths and weaknesses of each. The results are summarized as follows.

HealthClockface was described by 75% of participants as being visually engaging, described as “eye-catching,” “creative,” and “motivating.” Its ambient design was well-suited for glanceable use, with users appreciating its ability to blend into daily life. As P12 noted, “It doesn’t interrupt me but still makes me aware.” However, some, especially caregivers, found the abstract visuals confusing or overwhelming when quick interpretation was needed. Concerns were also raised about visibility in bright light and potential battery drain.

The numerical display was valued by 71.9% for its simplicity, clarity, and speed, particularly by caregivers who emphasized the need for precise communication. As C2 stated, “It’s easier to understand the numerical data and follow any changes." However, some patients found it unengaging, describing it as "bland" or "boring," and suggested adding contextual cues or alerts for better usability.

Reactions to the graphical background were mixed. Some participants appreciated its ability to convey trends over time and found it more engaging than plain numbers. C8 noted, "It shows trends, so it's easier to grasp complex information at a glance." This suggests some potential for glanceable interpretation in longer-term health monitoring. However, others, especially those unfamiliar with graphs, found it harder to interpret quickly. About half of the participants described it as "confusing" (P30) or "hard to read" (P6), which limited its usefulness in glance-based scenarios.

5 Discussion

Our findings demonstrate the potential of abstract, dynamic glanceable visualizations to support non-expert users and informal caregivers in engaging with personal health data. Participants responded positively to HealthClockface, describing it as both visually appealing and informative. This reinforces prior work on the role of aesthetics in promoting engagement and emotional connection in health technologies (Shelton & Nesbitt, 2016).

5.1 Supporting Awareness Through Glanceable Feedback

Unlike conventional health dashboards that require users to inspect the data in mobile applications, HealthClockface offers glanceable feedback directly on the smartwatch face, supporting quick, lightweight awareness of health data during routine interactions. This aligns with the goals of ambient information systems, which aim to shift user interaction from active monitoring to ambient awareness (Pousman & Stasko, 2006). Participants reported that the dynamic clockface encouraged regular reflection on their activity and heart rate, often without needing to launch separate apps. This kind of low-effort engagement may be particularly relevant for non-expert users, who may find traditional graphs or metrics difficult to interpret (Simblett et al., 2024; Cajamarca et al., 2023). By embedding health information within an existing routine interaction, HealthClockface offers a more accessible alternative to traditional health tracking tools.

While HealthClockface was generally perceived as easy to access and integrate into daily routines, some participants, particularly caregivers, expressed uncertainty about interpreting abstract patterns. These concerns suggest that while the visualization was glanceable and aesthetically engaging, its comprehensibility varied across users. Importantly, several participants noted that the meaning of the visuals became clearer with explanation or imagined repeated use, suggesting a short learning curve rather than a fundamental usability issue. This points to the need for initial onboarding or embedded explanations (e.g., tappable tooltips or tutorial overlays) to support early comprehension. Designing for progressive disclosure, where more meaning is gradually revealed over time, may also help balance expressiveness with interpretability, especially for users unfamiliar with abstract visualizations.

5.2 Balancing Abstract Expression and Informational Value

Participants appreciated the generative visuals as both motivating and glanceable, yet some questioned whether abstract patterns provided sufficient detail for decision-making. This tension reflects a broader challenge in artistic data visualization: the balance between abstraction and interpretability. Prior systems like UbiFit Garden (Consolvo et al., 2008) have leaned heavily into metaphor, often at the expense of direct data transparency. HealthClockface attempts to strike a middle ground by mapping physiological signals onto visually expressive patterns that still reflect meaningful trends (e.g., increased movement intensity or elevated heart rate). Future iterations might explore hybrid designs that offer layers of information, for instance, by combining abstract ambient visuals with tappable access to more detailed metrics.

Our findings also suggest that user preferences and interpretive needs vary significantly. Some participants valued the abstract aesthetic for its unobtrusiveness and emotional resonance, while others desired clearer, more explicit representations to better support health monitoring and caregiving tasks. These observations indicate that a one-size-fits-all approach is unlikely to meet the diverse needs of potential users. Future iterations should allow customization based on individual preferences and contexts, which could help accommodate different cognitive styles, informational goals, and situational demands, enhancing both the utility and appeal of such health visualizations.

5.3 Designing for Micro-Displays

Our results demonstrate that expressive, data-driven visuals can be effectively deployed even within the tight constraints of a smartwatch interface. Participants reported that the animation was readable and informative, despite the small screen size. This supports emerging work on glanceable interaction design for wearables (Blascheck et al., 2021), showing that meaningful feedback can be delivered through short, repeated interactions. At the same time, the smartwatch form introduces challenges, especially when multiple data streams need to be communicated simultaneously. Some participants noted that interpreting the visual while on the move or during busy moments could be difficult. Future research could explore how similar dynamic visualizations might scale to other platforms, for example, smartphone widgets or tablet lock screens, where more space allows for richer interaction without sacrificing glanceability.

5.4 Limitations and Future Work

Although the findings of this study are generally positive, several limitations should be considered. First, the study was conducted remotely, meaning participants did not have direct hands-on interaction with the smartwatch prototype. While the use of visual materials and guided demonstrations allowed for a broader reach and a relatively diverse sample, this approach may have limited participants' ability to fully assess the system's interactive features and real-world usability. This study primarily focused on exploring the potential of glanceable visualizations for personal health monitoring on smartwatches. Future work should evaluate their effectiveness through in-situ studies where participants use HealthClockface in their everyday lives to assess its practical value and integration into daily routines. Future research could also explore customization (e.g., letting users choose or design their own visual forms), long-term engagement, and broader applications such as stress monitoring or mood tracking.

Furthermore, while chaotic attractors inspired the generative visuals, the mapping between data and visual form was designed for expressiveness rather than analytical precision. This metaphor served as an aesthetic and structural foundation, not as a strict scientific model. Nonetheless, chaos theory may offer deeper value in representing nonlinear dynamics in health data (Biswas et al., 2018; Muhammet et al., 2019). Interdisciplinary research could explore how chaotic structures might encode complex physiological rhythms in meaningful ways.

6 Conclusion

This paper introduced HealthClockface, a smartwatch clockface that offers glanceable visualizations of health data using abstract and dynamic visuals generated by chaotic attractors. HealthClockface transforms real-time heart rate and activity level data into ambient, glanceable feedback within the frame of a digital clock face. The user study suggested that participants generally appreciated the aesthetics and found the visualizations helpful for maintaining awareness of their health status. The visuals were described as engaging and non-intrusive, supporting brief and frequent check-ins. However, the abstract nature of the visualization raised concerns about comprehensibility, especially in contexts requiring more precise or actionable information. These findings highlight both the potential and the limitations of glanceable feedback in health-tracking systems. Overall, this study contributes to the growing exploration of health data representations that move beyond charts and metrics and expand the design space for glanceable and ambient visualizations on wearable devices. The insights from this work can inform the future design of ambient information systems that balance visual appeal, clarity, and utility in supporting health monitoring and reflection.

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