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Adaptive Systems for Well-being Promotion: A Systematic Mapping

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Abstract. Research on Human-Computer Interaction (HCI) interfaces has gained increasing relevance in both corporate and academic environments, particularly in adaptive systems that offer personalized interventions. Adaptive systems are crucial for enhancing user experience and promoting well-being by dynamically adjusting to individual needs and contexts. Well-being, which encompasses physical, mental, and social dimensions, can significantly influence user behavior and task performance. However, measuring well-being remains a complex challenge due to its subjective and multidimensional nature. This study aims to map and analyze the state of the art in computational interfaces that adapt to the user's context to promote well-being. Specifically, the study addresses the gap in adaptive systems, which are still underdeveloped in the field. Despite significant progress in measuring well-being, most systems focus on monitoring well-being states or training predictive models, rather than offering fully adaptive interventions. To explore this, a systematic mapping study was conducted, investigating three key questions: What is the purpose of the study regarding the well-being dimension explored, as well as the approaches and techniques used to promote it? What methods were employed to measure users' well-being? What interventions were implemented to promote well-being? The analysis of 36 selected studies reveals that research primarily concentrates on the mental and physical dimensions of well-being, with artificial intelligence techniques and physiological sensors, particularly electrocardiograms (ECG), being the most frequently used. However, there is a notable lack of adaptive systems in the literature. These findings underscore the need for further development of adaptive interventions that actively improve well-being, providing valuable insights to guide the design of adaptive interfaces. By leveraging these insights, future systems can be developed to enhance user experience and promote well-being across diverse domains.

Keywords: Well-being, Adaptive system, Physiological sensors, Systematic mapping

1 Introduction

The study of interfaces within the field of Human-Computer Interaction (HCI) has gained increasing prominence in both corporate and academic environments. Traditionally, system design has prioritized functionality, often relegating the user interface to secondary importance [Norcio and Stanley, 1989]. In conventional computational systems, users are expected to adjust their behavior and problem-solving strategies to the system, rather than the system adapting to the user [Norcio and Stanley, 1989]. However, it has long been recognized that ideal computer systems should adapt to the user, compensating for weaknesses, providing context-appropriate assistance, and reducing the user's cognitive and physical load [Norcio and Stanley, 1989; Carrera-Rivera *et al*., 2025].

Despite this recognition, the development of truly adaptive systems remains a challenge. Various terminologies are used in the literature to describe interfaces that adapt based on interaction characteristics, user needs, or context. The term "intelligent interfaces" is used by Maybury [1998] to describe "human-machine interfaces that aim to improve the efficiency, effectiveness, and naturalness of human-machine interaction by representing, reasoning, and acting on models of the user, domain, task, discourse, and media (e.g., graphics, natural language, gesture)". Similarly, Völkel *et al*. [2020] conducted a meta-analysis exploring the term "intelligen*" in relation to interface, as well as its co- occurrences with other descriptions (e.g., "adaptive"). In their work, these interfaces encompassed various types of technology, such as "system", "tool", "agent", or components like "interface", "technique", "algorithm." These entities include both intelligence within the interface and internal intelligence within the system. A variety of co-descriptors were also identified to describe the characteristics of these entities, such as user-adaptive, interactive, natural, and automatic, as well as automated, autonomous, context-sensitive, context-dependent, multimodal, real-time, and context-aware. In this sense, the adaptation of the interface based on interaction characteristics, user needs, or usage context reflects a mixed understanding of the term, leading to a non-uniform usage, which can even be observed in the term "adaptive intelligent user interfaces" [Raheel, 2016].

This lack of standardization in terminology reflects a fragmented understanding of adaptation, with some works distinguishing between "adaptive" and "intelligent" interfaces. Brdnik *et al*. [2022] argues that while many intelligent interfaces can be described as adaptive interfaces, not all adaptive interfaces are intelligent.

Systems can be adapted either manually by the user or dynamically by the system. Adaptable systems allow users

to modify and personalize the interface, capturing emerging needs but placing the adaptation burden on the user [Fischer, 2023].

In contrast, adaptive systems leverage context-aware technologies to dynamically adjust to users, their tasks, and the surrounding environment, ensuring an improved user experience [Fischer, 2023; Galindo *et al*., 2017].

Several studies introduce different terms for adaptive interfaces, such as smart, context-sensitive, multimodal, flexible, self-adaptive, adaptable user interfaces, recommender systems, intelligent tutoring systems [Gonçalves *et al*., 2019; Sanchez *et al*., 2017; Van Velsen *et al*., 2008; Schlungbaum, 1997; Wang and Stroulia, 2003; Innocent, 1982; Fischer, 2023].

While these classifications provide useful distinctions, they also highlight the complexity of adaptation, particularly when the goal is to enhance user well-being. Well-being is a multidimensional construct that includes emotional, occupational, physical, social, intellectual, and spiritual aspects [Strout and Howard, 2012]. Kiefer [2008] further categorizes well-being into physical, mental, and social dimensions, emphasizing their interdependent nature. This article adopts Kiefer's classification of well-being on these dimensions.

In the context of adaptive interfaces, user well-being is influenced by various factors, including emotions, cognitive load, and interaction experience [Galindo *et al*., 2017]. However, measuring well-being is inherently complex, as it involves subjective experiences that are difficult to quantify. Given these challenges, this study identifies and analyzes the state of the art in computational interfaces designed to promote user well-being.

While adaptive interfaces have been a subject of study for decades, recent advancements in artificial intelligence and context-aware computing have renewed interest in their potential to enhance user experiences. In particular, the role of adaptive interfaces in promoting user well-being remains an underexplored yet critical area of research. This study aims to address this gap by systematically reviewing computational interfaces designed to adapt in ways that support user well-being. Understanding how well-being is considered, the dimensions frequently explored, the methods used to measure well-being, and the interventions implemented are essential for advancing this field.

These considerations add complexity to the process of interface adaptation, especially when the goal is to promote user well-being. Previous literature reviews have investigated various aspects of adaptive and intelligent interfaces. However, there is a lack of comprehensive reviews focusing specifically on how such interfaces address user well-being. While studies have examined adaptive user interfaces [Gonçalves *et al*., 2019; Sanchez *et al*., 2017], context-sensitive interfaces, and recommender systems [Fischer, 2023], their relevance to well-being has not been systematically analyzed.

This study examines computational interfaces designed to enhance user well-being and is guided by three research questions derived from gaps highlighted in prior reviews.

The first research question examines the objectives of the studies in relation to the dimensions of well-being, as well as the approaches and techniques implemented in computational interfaces to enhance these dimensions. Previous reviews have offered valuable contributions but were typically limited to specific domains, populations, or methodological niches, such as older adults El Kamali *et al*. [2020], young adults Meegahapola and Gatica-Perez [2020], smartphone sensing Cornet and Holden [2018], or machine learning methods Oyebode *et al*. [2023]. These narrower perspectives yielded partial insights without mapping the broader landscape of objectives and techniques. To address this gap, the first research question focuses on providing a more integrative synthesis across contexts.

The second research question examines how well-being has been assessed in the analyzed studies, systematizing the strategies employed. Although methodological aspects have been discussed previously, emphasis varied and left important gaps. For instance, Meegahapola and Gatica-Perez [2020] emphasized sensing modalities rather than assessment methods; Oyebode *et al*. [2023] focused on data collection, machine learning techniques, and model evaluation without consolidating well-being assessment approaches; Cornet and Holden [2018] highlighted smartphone sensors and validation procedures but did not provide a structured synthesis of subjective and objective measures. The current review builds on these contributions by offering a systematic mapping of assessment strategies that earlier work acknowledged but did not consolidate.

The third research question explores the interventions implemented in the studied solutions. Most prior reviews either did not detail intervention strategies (El Kamali *et al*. [2020]; Meegahapola and Gatica-Perez [2020]; Oyebode *et al*. [2023]) or described them only in terms of limited feedback mechanisms, such as passive sensing Cornet and Holden [2018]. A comprehensive analysis of concrete intervention mechanisms remains absent in the literature. The current review addresses this gap by synthesizing how interventions have been conceptualized and applied.

Taken together, these three questions directly address gaps left by prior reviews, thereby advancing the HCI literature. By systematically reviewing existing work, this study provides a clearer overview of current trends, methodological limitations, and intervention strategies. The findings contribute to the HCI community by clarifying how adaptive interfaces can support user well-being and by identifying promising directions for future research and design. These aspects are further elaborated in the related work section.

This article is structured as follows. The next section presents related work, providing context for our study. We then describe the research method, detailing the selection of articles and the data extraction process. Next, we present the results, addressing the research questions through analysis and discussion. Finally, we conclude with a discussion of the implications of our findings for adaptive systems aimed at enhancing user experience and promoting well-being, along with directions for future research.

2 Related work

Several systematic reviews have explored computational approaches to promoting well-being, each with distinct focuses, techniques, and intervention strategies. This section discusses

four related works, highlighting commonalities and key differences from the present review. El Kamali *et al*. [2020] reviewed virtual well-being coaches for older adults, analyzing 56 studies across physical, nutritional, cognitive, social, and emotional domains. Their findings emphasize a gap in multidomain e-coaching evaluations, despite older adults' appreciation for conversational agents and robots.

Meegahapola and Gatica-Perez [2020] examined smartphone sensing for young adults' well-being, reviewing 26 studies covering emotion, mood, stress, depression, anxiety, eating behavior, alcohol use. They categorized studies into data-driven (passive sensing and self-reporting) and system-driven (smartphone applications) approaches. Their findings highlight smartphones' potential for emotional well-being monitoring, with accelerometers frequently used for behavioral proxies but less for mental and social dimensions.

Oyebode *et al*. [2023] focused on adaptive systems based on Machine Learning (ML) for health and well-being, analysing 87 studies. They classified data collection methods, ML techniques, and adaptive strategies. Most studies used smartphone and wearable sensors, with classical ML techniques prevalent. A key gap identified was that 78% of studies did not evaluate intervention effectiveness.

Cornet and Holden [2018] reviewed 35 studies on smartphone-based passive sensing for health and well-being, primarily in mental health, sleep, and general health. They classified data collection and analysis techniques, noting that many studies lacked user feedback. Among those providing feedback, graphical data presentation was common, while personalized messages were rare. They concluded that passive sensing has significant potential for clinical applications due to its accuracy and low intrusiveness. Although these reviews align with the present study in exploring well-being and including PubMed as a data source, they differ in scope. The present work uniquely incorporates Springer Link, employs a broader search window, and does not limit itself to specific populations (e.g., older adults in El Kamali *et al*. [2020], or young adults in Meegahapola and Gatica-Perez [2020], data collection methods (e.g., smartphone sensing in Cornet and Holden [2018], or analytical techniques (e.g., ML in Oyebode *et al*. [2023]).

The studies analyzed various well-being domains, including physical [El Kamali *et al*., 2020; Meegahapola and Gatica-Perez, 2020], nutritional [El Kamali *et al*., 2020], cognitive [El Kamali *et al*., 2020], social El Kamali *et al*. [2020]; Meegahapola and Gatica-Perez [2020], emotional [El Kamali *et al*., 2020], and mental health [Meegahapola and Gatica-Perez, 2020]. Health was also examined alongside well-being [El Kamali *et al*., 2020; Oyebode *et al*., 2023; Cornet and Holden, 2018]. This study focuses on mental, social, and physical well-being, aligning most closely with Meegahapola and Gatica-Perez [2020].

A key gap in existing reviews is the lack of explicit well-being stimulation strategies. Most studies [El Kamali *et al*., 2020; Meegahapola and Gatica-Perez, 2020; Oyebode *et al*., 2023; Cornet and Holden, 2018]do not specify these approaches. In contrast, this mapping categorizes multimodal stimulation models, including audio, video, physical activities, and relaxation techniques.

Regarding system architecture, related work classifies computational solutions into monitoring, processing, and intervention [El Kamali *et al*., 2020]; analytical and feedback-based systems [Meegahapola and Gatica-Perez, 2020]; and domain-structured solutions [Oyebode *et al*., 2023]. This study synthesizes these approaches by characterizing systems in terms of monitoring, interaction, and adaptive responses. While Oyebode *et al*. [2023] is the most similar in focusing on adaptive systems, it is restricted to ML-based classification, whereas this study explores adaptive systems more broadly.

Interventions in related reviews are either limited to passive feedback [Cornet and Holden, 2018] or remain unspecified [El Kamali *et al*., 2020; Meegahapola and Gatica-Perez, 2020; Oyebode *et al*., 2023]. Additionally, existing studies classify sensors based on collection methods—such as smartphone, wearable, and non-wearable sensors [El Kamali *et al*., 2020; Meegahapola and Gatica-Perez, 2020; Oyebode *et al*., 2023] — but do not specify whether they are commercial or homemade. This study advances the discussion by detailing sensor types and their commercial availability.

In summary, this systematic mapping expands on previous reviews by detailing stimulation strategies, broadening the scope of adaptive computational solutions beyond ML-based techniques, and encompassing a wider range of data collection methods beyond smartphones. Moreover, it uniquely investigates intervention mechanisms to enhance well-being. By analyzing intervention strategies, this study contributes to improving system adaptability and effectiveness, fostering more personalized and context-aware user experiences.

3 Research method

To ensure relevance and scientific rigor, the systematic mapping followed the method proposed by [Petersen *et al*., 2008], which outlines key steps such as defining research questions, searching for relevant articles, screening and classifying abstracts by keywords, and extracting and mapping data.

This study was guided by three research questions, designed to address key gaps in the literature on adaptive systems for well-being, with a focus on study scope, methods, and interventions:

- RQ1: What is the purpose of the study in relation to the well-being dimension explored and the strategies employed to promote it?
- RQ2: What methods were used to measure the user's well-being?
- RQ3: What interventions were implemented?

Given the complexity and multidimensionality of well-being, these research questions aimed to provide a structured and comprehensive analysis of existing approaches.

3.1 Article selection

Four publication databases were surveyed: IEEE Computer Society, ACM Digital Library, Springer Link, and PubMed. These databases were selected due to their relevance as data sources for Computer Science, their reliability, and their widespread use in the literature.

As pointed out in the introduction, various terminologies are used to describe interfaces that adapt according to the characteristics of interaction, user needs, or usage context. According to Völkel *et al*. [2020], terms like application, algorithm, system, agent, etc., were frequently used for this purpose, as well as terms like complex, real-time, multimodal, context-aware, natural, dynamic, interactive, adaptive. The authors observed that such terms are often used together with the term adapt*. Following Völkel *et al*. [2020], different combinations of keywords were tested in this article, initially opting for string 1 (Table 1).

Table 1. String 1

(“abstract”:flexible or “abstract”:intelligent or “abstract”:context) and (“abstract”:interface or “abstract”:system or “abstract”:agent) and “abstract”:adapt*) and (“all-metadata”:well-being or “all-metadata”:wellbeing)

Source: authors

This initial string proved to be too broad, returning a large number of articles outside the scope and not satisfactorily meeting the inclusion criterion (CI2), which required the co-occurrence of the terms adapt* and well-being in the abstract. Based on these initial results, the keywords from the relevant articles were combined to create string 2 (Table 2), which proved to be more specific. CI2 was adjusted to include articles with the terms well-being or wellness in the abstract or title. In the SpringerLink database, the search was conducted across all fields instead of just the abstract due to the platform not offering specific filters in the advanced search. Additionally, further criteria were applied due to the large number of articles returned. First, only the area of Computer Science was selected, and then a reduction criterion was applied, which involved sorting the articles by relevance and stopping the review after 50 consecutive articles did not meet CI2.

Table 2. String 2

(“abstract”:“conversational interface” or “abstract”:“recommend* system*” or “abstract”:“intelligent user interfaces” or “abstract”:“intelligent systems” or “abstract”:“smart system” or “abstract”:“intelligent agent” or “abstract”:“smartagent” or “abstract”:“adapt* system” or “abstract”:“adapt* visualization” or “abstract”:“adapt* interfaces” or “abstract”:“adapt* agent” or “abstract”:“user-centric adapt*” or “abstract”:“flexible interfaces” or “abstract”:“personalized recommendations” or “abstract”:“personalized system” or “abstract”:“persuasive app” or “abstract”:“prediction system” or “abstract”:“persuasion technologies” or “abstract”:“emotion management system” or “abstract”:“emotion agents” or “abstract”:“emotion recognition” or “abstract”:“emotion classification” or “abstract”:“well-being rating” or “abstract”:“wellbeing rating” or “abstract”:“measure wellbeing” or “abstract”:“behavior-context prediction” or “abstract”:“user-centric intervention” or “abstract”:“tangible interfaces” or “abstract”:“autonomous agents” or “abstract”:“autonomous systems” or “abstract”:“physiological signal*” or “abstract”:“physiological sensory” or “abstract”:“bio-signals” or “abstract”:“biosensors” or “abstract”:“wearable sensor” or “abstract”:“wearable technology”) and (“abstract”:“well-being” or “abstract”:“wellbeing” or “abstract”:“wellness”) or (“document title”:“wellbeing” or “document title”:“wellbeing” or “document title”:“wellness”)

Source: authors

This iterative refinement of search strings aimed to balance sensitivity and specificity, ensuring comprehensive coverage of relevant studies while minimizing irrelevant results. By leveraging keywords from the literature and refining them based on initial search outcomes, we systematically optimized the retrieval process to align with the research objectives and inclusion criteria.

The inclusion and exclusion criteria (Table 3) adopted in this review follow established methodological practices for systematic literature reviews and are consistent with previous studies in the field. They were defined to ensure both the relevance and quality of the studies selected, while maintaining the focus on adaptive computational interventions for user well-being. The inclusion criteria required complete articles published in peer-reviewed journals, ensuring methodological rigor and scientific reliability [Oyebode *et al*., 2023; Cornet and Holden, 2018; El Kamali *et al*., 2020]. In addition, eligible studies had to contain at least one term from the predefined search string in the title or abstract, together with the terms adapt* and well-being. This procedure, previously adopted in related reviews (e.g., [El Kamali *et al*., 2020], was employed to ensure alignment between the selected studies and the scope of the present review.

Exclusion criteria targeted outdated works, eliminating papers published more than a decade ago to ensure contemporaneity [Oyebode *et al*., 2023; Meegahapola and Gatica-Perez, 2020]. Only studies published in English were retained to guarantee linguistic uniformity and comparability [Cornet and Holden, 2018; El Kamali *et al*., 2020; Meegahapola and Gatica-Perez, 2020]. Works that did not address human-centered interventions, lacked empirical validation, or presented incomplete data were also excluded, reinforcing the consistency and applicability of the findings. Finally, the full text of each article was examined to confirm adherence to the research scope, following procedures adopted in prior reviews [El Kamali *et al*., 2020].

This process was initially conducted by one researcher, and subsequently validated by the research team. Discrepancies were resolved through discussion and consensus.

The initial search identified 11,162 articles. After applying the inclusion and exclusion criteria in two stages, the sample was first reduced to 1,090 articles (IC1 and EC1–EC4) and then to a final set of 36 articles (IC2 and EC5–EC7), as summarized in Figure 1 with the search completed in April 2024.

Table 3. Inclusion and exclusion criteria used in systematic mapping

Inclusion criteria	Exclusion criteria
IC1: full-text articles published in journals; IC2: articles that included at least one of the terms from the search string in the title or abstract, along with the terms ”adapt*” and ”well-being.”	EC1: articles published before 2014; EC2: incomplete articles; EC3: articles in a language other than English; EC4: articles in which the computational intervention was not performed on human subjects; EC5: articles whose abstract is not related to the research questions and the study’s objective; EC6: articles whose body is not related to the research questions and the study’s objective; EC7: non-empirical works.

Source: authors

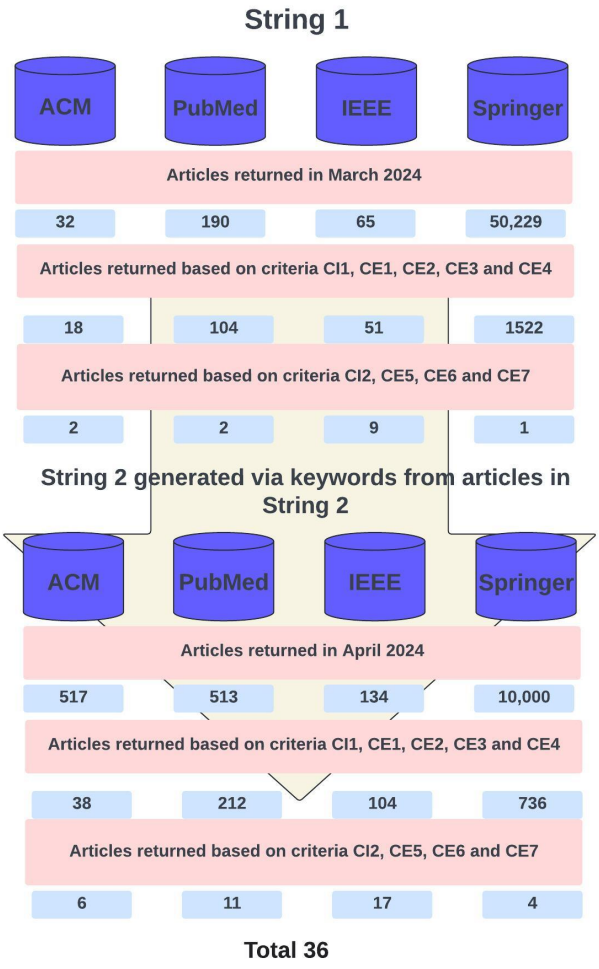


Figure 1. Steps and resulting articles
Source: authors

The distribution of the 36 articles by publication year shows a growing focus on user well-being over time, peaking in 2021 and experiencing a slight decline in 2022, as presented in Figure 2.

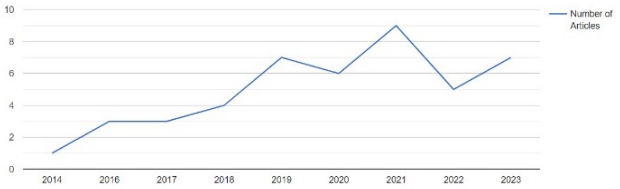


Figure 2. Distribution of articles by year
Source: authors

The database with the highest occurrence of publications is IEEE, accounting for one-third of the articles, followed by PubMed, with 23% of the articles (see Figure 3).

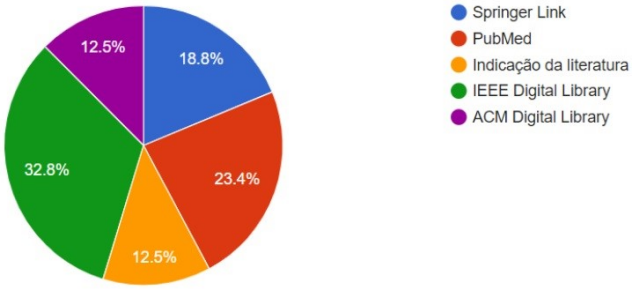


Figure 3. Distribution of articles by databases
Source: authors

3.2 Data extraction

After applying the inclusion and exclusion criteria, the researchers conducted a full-text review of the 36 selected articles. To ensure a systematic and rigorous data extraction process, a structured protocol was followed, as outlined in the data extraction form, presented in Table 4. This protocol guided the identification of publication metadata, study objectives, approaches and interventions, contexts of use, participant details, well-being measurement methods, results, and reported limitations or gaps.

Table 4. Data extraction form

Item	Categories
Publication data	title, publication vehicle, author and institutional affiliation, year of publication
Purpose of the study	describe the purpose of the study; specify whether the focus is on user well-being or positive emotions.
Type of approach	• type of adaptation: dynamic, by the system itself, or by the user, among others. • used AI, static rules, types of algorithms, among others. • Type of intervention (general): how the solution generates the intervention, such as recommendations for physical activity, dietary suggestions, calls to family members, among others.
Context of Use	description of the usage environment (location)
Number of Participants	number of participants in the study.
Well-being measurement methodology	how well-being assessments were conducted, identifying: • objective elements: – sensors: ECG, ECC; among others; – homemade (developed by the group) or commercial; – signals captured from the sensors; – signal preprocessing such as filters, thresholds, and classification; • subjective elements: questionnaires, interviews, observation, among others.
Results	describe the key outcomes related to user well-being and how they align with the study objectives
Limitations and gaps	describe limitations and challenges, including recommendations for future work.

Source: authors

The initial extraction followed a multilayered strategy to enhance accuracy, reliability, and reproducibility. Two researchers worked in parallel, independently applying an open-coding approach by systematically answering each question in the protocol and generating preliminary codes. These codes were compared and refined through discussions among the researchers, aiming for consensus and mitigating potential biases such as individual interpretation of relevance criteria. Each researcher was responsible for coding approximately half of the articles. After this stage, the sets were exchanged so that each researcher validated the other's classifications. This cross-checking allowed for the early identification of discrepancies. Divergences were first resolved between the two coders; if consensus could not be reached, the cases were presented to a third researcher. Finally, the complete set of codes and classifications was subjected to collective validation, ensuring internal coherence and reinforcing the analytical framework.

After extraction, the results were organized based on the three research questions (RQ1–RQ3) and their sub-questions, as outlined in the data extraction form (Table 5).

Table 5. Research questions and subquestions

- RQ1: What are the objectives of the studies concerning dimensions of well-being, and what approaches and techniques are employed in computational interfaces to enhance these dimensions?
  - SRQ1(a): What dimensions of well-being are addressed in the studies?
  - SRQ1(b): What are the main stimuli used to promote well-being? Examples may include audio, video, physical activity, relaxation activities.
  - SRQ1(c): How does the interface behave? For example, did the solution adapt to the user's context, offer recommendations, or merely monitor user information?
  - SRQ1(d): What are the main techniques utilized in the proposed solutions? Examples include Artificial Intelligence, Virtual Reality, Big Data, among others.
- RQ2: What methods were used to measure user's well-being?
  - SRQ2 (a): How was well-being assessed, this encompasses:
    - Subjective measures, including questionnaires, interviews, observations, and other similar methods.
    - Objective measures, such as facial expression analysis, Electroencephalography (EEG), ECG, Electrodermal Activity (EDA), among other related techniques.
    - Source of technology: is the technology developed in-house (homemade) or is it commercially available?
- RQ3: What interventions were implemented in the developed solutions?
  - SQP3 (a) What interventions were implemented? Examples include recommendations for physical activity, dietary suggestions, calls to family members, and others.
  - SQP3 (b) How did the solution generate the intervention? Examples include SMS, audio messages, emails, pop-ups, and others.

Source: authors

4 Results

Table 8 (APPENDIX) presents the 36 selected articles with identifiers (ID), authorship and year of publication, and title.

The content analysis of the abstracts from the 36 articles highlights the most frequently used terms, as shown in Figure

4, excluding those terms defined by the inclusion criterion IC2. The most recurrent terms were “health” (47), “interventions” (45), “stress” (40), and “emotion” (37). Other frequent terms such as ”sensors” (26), ”wearable” (26), and ”physiological” (24) reflect the predominance of physiological sensing approaches (Figure 4).



Figure 4. Incidence of terms in abstracts
Source: authors

A significant variation in sample size was observed across these studies, with the smallest sample consisting of only one participant and the largest comprising 605 participants. The average sample size was 59, with a median of 25 participants, and 75% of the studies involved samples of up to 50 participants.

While all studies focus on well-being, they differ in methodologies, technologies, and application contexts. These differences can be observed in their objectives, target domains, and methods. Figure 5 (Sankey diagram) systematizes the most frequent relationships between well-being dimensions, stimuli, sensors, and system behaviors. As shown, mental well-being is most often linked to natural and visual stimuli, measured predominantly with ECG and EDA sensors, while physical well-being is more frequently associated with activity and environmental monitoring. Social well-being, in contrast, appears rarely and is connected to fewer types of sensors or adaptive system behaviors.

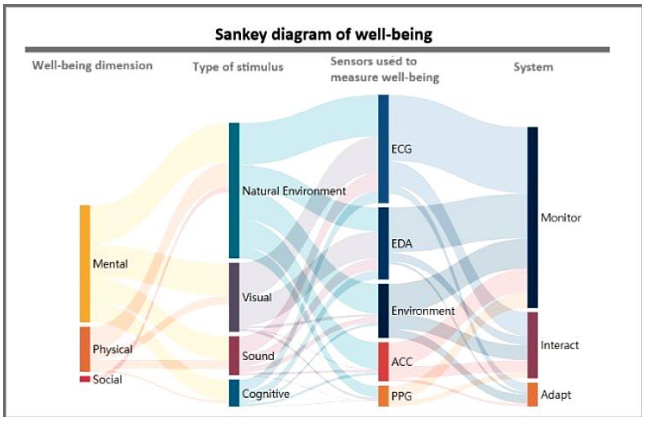


Figure 5. Relationships between Well-Being Dimensions, Sensors, Stimuli, and Systems in the Reviewed Studies
Source: authors.

Physiological signals such as ECG and EDA dominate the measurement methods, often analyzed with machine learning classifiers. Neural networks, SVM, random forests, k-NN, and decision trees are the most frequent algorithms. Studies applied these algorithms to emotion recognition, stress detection, and personalized feedback, with different levels of accuracy depending on the context and data quality.

The choice of technologies varied according to context: VR/AR appeared in a minority of studies, while wearables and mobile sensing were more common.

Regarding system behaviors, different approaches were identified, including monitoring, user interaction, and contextual adaptation. Most systems performed only monitoring, 39% included some form of interaction, and only 11% provided adaptive responses.

In summary, technological approaches to promoting well-being vary in terms of targeted well-being domains, methods, application contexts, and techniques.

Overall, mental well-being was the predominant focus, particularly through natural environment stimuli. ECG sensors were the most frequently used for well-being assessment, and monitoring was the main system behavior, with fewer occurrences of interaction or adaptation. These findings are further examined in the Discussion section, where they are organized according to the three research questions (RQ1–RQ3).

4.1 Discussion

4.1.1 RQ1: Dimensions of Well-being, Approaches, and Techniques Employed in Computational Interfaces

The objective of the first question was to identify the primary dimensions of well-being explored in the reviewed studies. This was accomplished by applying the ecological dimensions of physical, social, and mental well-being as outlined by Kiefer [2008].

For physical well-being, both the user’s physical fitness and functional aspects were considered, along with solutions aimed at improving health through suggestions for physical activities and healthy eating habits. In the social dimension of well-being, factors related to social interaction were considered, including hobbies, leisure, social participation, family, and social networks. For mental well-being, affective aspects, such as stress levels, mental health, feelings of depression, as well as psychological and spiritual factors, were taken into account. If the well-being dimension was not explicitly mentioned, we analyzed the study’s objectives to infer the corresponding dimension.

Figure 6 presents the dimensions of well-being extracted from the reviewed studies. The most explored dimension in computational solutions was mental well-being. Among the analyzed articles, 86% address the user’s mental well-being, focusing on topics such as affective state [07][08][11][19][25][26][28][32][34] and stress [01][03][21][22][23][27][32]. Physical well-being appears in 36% of the studies, with main topics being healthy eating habits [01][05][10] and physical activity [01][04][05][10][29][31]. Only two papers explored social well-being [04][10], representing 6% of the reviewed articles.

In addition to the dimensions, information was extracted

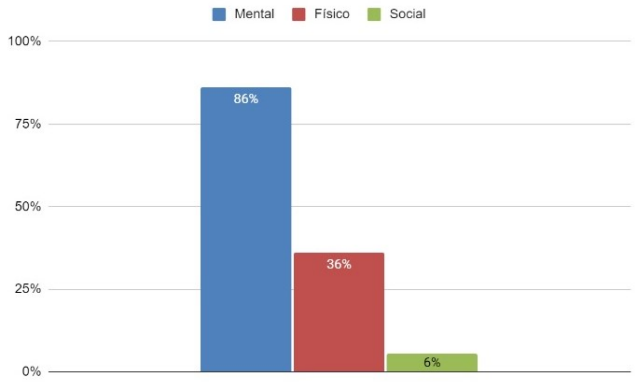


Figure 6. Percentage of articles according to well-being dimension*
Source: authors.
*The total exceeds 100% because the same article can address more than one dimension

regarding the primary stimuli used to assess user well-being. Examples include visual stimuli (images and videos), cognitive stimuli (games, puzzles, reading, and text transcription), and auditory stimuli (music, meditation audio). The category ”natural environment” was used to classify those computational solutions that monitor the user in their daily routine to assess their well-being without employing specific stimuli.

As shown in Figure 7, the natural environment was the most frequently used approach in the reviewed studies [03][04][08][10][12][13][14][16][17][22][27][31][32][33][34][35][36], followed by the use of visual stimuli, particularly videos [02][07][19][20][24][25][33], auditory stimuli [01][02][06][09][11][23][30][36], and cognitive stimuli [05][11][15][20][21][28][30].

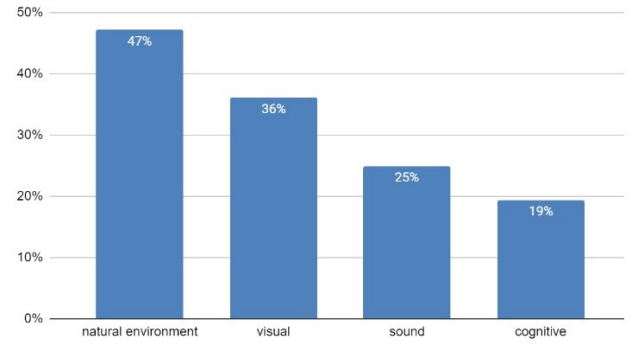


Figure 7. Percentage of articles according to the type of stimulus used*
Source: authors.
*The total exceeds 100% because the same article can use more than one stimuli

Studies classified as ”natural environment” assessed users in their daily activities and routines. For instance, study [4] monitored users’ physiological data for 24 hours using the Jawbone wearable, along with data from social media usage and the environment itself. This included step count, sleep duration and quality, number of tweets, atmospheric pressure, precipitation, temperature, humidity, etc. Another example is [17], which continuously monitored elderly users in a nursing home using a commercial wearable device (Sony SmartBand 2), collecting data on heart rate, step count, and sleep duration and quality.

Studies classified under visual stimuli utilized videos or images. For example, study [24] employed video clips selected from the site ”last.fm”, which provides a classification of emotional reactions for each video clip based on adjectives characterizing emotional states (sad, happy, cheerful, etc.), attributed by users worldwide. The authors selected 10 video clips, each thirty seconds long, for each emotional quadrant (high valence/high arousal — high valence/low arousal — low valence/high arousal — low valence/low arousal). Users were then asked to rate their affective reaction to these stimuli using the Self-Assessment Manikin (SAM) questionnaire. Another example of visual stimuli is [11], which used images from the International Affective Picture System (IAPS), a database providing a standardized set of images for studying emotions. The authors monitored users’ physiological signals while they were exposed to these images.

Studies employing auditory stimuli used a variety of sounds, including music, noise, relaxation audio recordings, and mindfulness exercise audios. For example, study [23] assessed the effects of different types of sounds on the balance of the autonomic nervous system. The stimuli included ambient music (nature sounds and soft melodies such as Crystal Waters by Halcyon Shores and Nocturne by LUVT), classical music (The Blue Danube, Op. 314 by Johann Strauss II), and metal music (Creeping Death by Metallica), as well as noise of varying frequencies and intensities. Users were exposed to 5-minute listening sessions for each music genre, with 1-minute breaks in between, followed by noise sessions. Physiological signals were collected during these sessions.

Studies utilizing cognitive stimuli were those that involved activities such as games, mathematical operations, puzzles, and autobiographical memory tests. For example, study [28] used the programming of a robot through interaction with an avatar on an iPad as a stimulus while capturing the emotional state of children with Autism Spectrum Disorder (ASD).

Many of the reviewed studies employed a combination of stimuli, such as [11][30], which used visual, auditory, and cognitive stimuli, and [2], which used both audio and video.

The goal concerning interface behavior was to assess whether the developed solutions adapt to the user based on their context, facilitate interactions between the user and the solution, or simply monitor the user. According to the classification applied in this mapping, an interface that adapts to the user based on context necessarily involves both monitoring and interaction; similarly, an interface that interacts with the user inherently involves monitoring.

As shown in Figure 8, most of the computational solutions in the reviewed studies only monitor the user, meaning they do not involve any interaction or adaptation. Just over one-third of the reviewed articles (39%) featured interfaces that interacted with the user [1][3][4][5][8][12][28][33][34][36], and only 3 of these studies (11%) included adaptations based on the user’s context [6][7][10][31].

One of the three studies in which the interface adapts to the user’s context is by Khattak *et al*. [2016], which developed a decision support system to generate personalized recommendations. The system used a smartphone, supported by wearable sensors, to recognize the user’s location, activities, and vital health data. After processing the data, the system could generate personalized recommendations for nutritional intake, physical activities (exercises), and future medical assistance and medication recommendations. The proposed system recognizes and learns from the environment but fo-

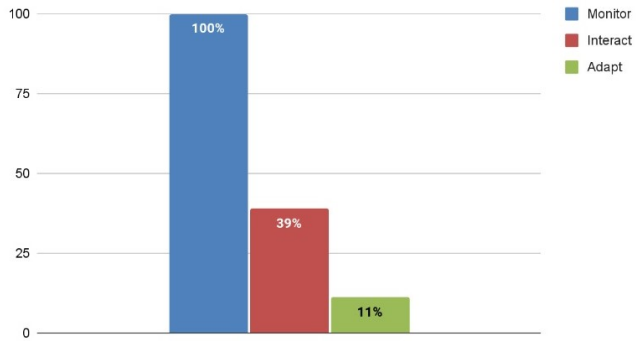


Figure 8. Percentage of articles according to interface behavior
Source: authors.

cuses on collecting and generating recommendation rules rather than on the recommendations themselves.

Regarding data analysis techniques, it was observed that the use of machine learning algorithms was the most frequent. These results align with the data on interface behavior, as most studies focus primarily on monitoring users. Thus, the collected data were mostly used to test and train artificial intelligence algorithms [5][6][7][8][11][13][15][17][18][19][20][21][22][23][24] [25][26][28][32][33][34][36]. Table 6 presents the algorithms used in each study. The most commonly used algorithms were neural networks (12 articles), followed by SVM (9 articles), RF (7 articles), k-NN (6 articles), and DT (4 articles).

Based on Table 6, most of the articles used supervised algorithms, with only one employing an unsupervised algorithm [36] and another using a self-supervised algorithm [34]. The obtained result aligns with the work of Oyebode *et al*. [2023], in which the vast majority of reviewed articles (82.94%) reported the use of supervised learning techniques.

Among the studies addressing adaptive systems, only two developed conversational interfaces with machine learning algorithms: Do *et al*. [2020], who employed Compact Feedforward Neural Networks, and Pham *et al*. [2021], who applied Neural Networks, Decision Trees (DT), Gradient Boosting, Support Vector Machines (SVM), and Radial-Basis Function Networks (RBF). In contrast, the works of Khattak *et al*. [2016]; Kraaij *et al*. [2020] neither address nor specify the use of such techniques.

The studies examined in Table 6 demonstrate significant challenges in the development of machine learning-based solutions, encompassing both fundamental issues related to data quality and representativeness, as well as practical implementation aspects. These challenges provide valuable insights for the development of machine learning solutions, particularly in sensitive domains such as well-being.

The analysis identified four main categories of challenges: data-related; inherent to modeling; technical and operational; and validation-related. Although this categorization is useful for analytical purposes, it is important to emphasize that these challenges are interconnected, requiring integrated approaches to overcome them.

The category of data-related challenges was the most recurrent, encompassing issues of quality, quantity, imbalance, and biases. The quality challenges include low temporal data resolution [22], presence of noise and anomalies [05][07][13], as well as missing or incomplete data [05] [22].

Table 6. Algorithms used

Item	Categories
[Henriquez *et al*., 2017]	RF (Random Forest); k-NN (K-Nearest Neighbors)
[Do *et al*., 2020]	Compact Feedforward Neural Networks
[Pham *et al*., 2021]	Neural network; DT (Decision Tree); Gradient Boosting; SVM (Support Vector Machines); RBF (Radial-Basis Network)
[Calatrava-Nicolás *et al*., 2021]	SVM
[Meza-Kubo *et al*., 2016]	Patternnet Neural Network
[Akhtar *et al*., 2023]	RNN (Recurrent Neural Network)
[Jin *et al*., 2020]	BLSTM (Bi-directional Long Short-Term Memory); LSTMs (Long Short-Term Memory)
[Yu *et al*., 2018]	ANN (Artificial Neural Network); L.SVM (Support Vector Machine with Linear); P.SVM (Support Vector Machine with Polynomial); R.SVM (Support Vector Machine with Radial Kernels); DT (Decision Tree)
[Chen *et al*., 2018]	AdaBoostM1; Multilayer Perceptron
[Alam *et al*., 2019]	CNN (Convolutional Neural Network)
[Martinez *et al*., 2019]	1R rule; DT; k-NN; NB (Naive Bayes), RBF; SVM; Ada Boost (AdaB); Bagging; RF; LR (Logistic Regression); MLP (Multi-Layer Perceptron)
[Aristizabal *et al*., 2021]	Neural Network (Keras 2.0)
[Booth *et al*., 2022]	EN (Elastic Net); RF; MLP (Feed-Forward Multi-Layer Perceptron); GRU (Gated Recurrent-Unit); LSTM (Long Short-Term Memory)
[Rodrigues *et al*., 2023]	NB; RF, DT; SVM; k-NN
[Rinella *et al*., 2022]	k-NN; SVM
[Pinto *et al*., 2020]	RF; Neural Networks
[Arabian *et al*., 2023]	SVM; CNN
[Ali *et al*., 2023]	SVM; k-NN; RF
[Li and Sano, 2020]	Deep Neural Network
[Dissanayake *et al*., 2022]	SigRep (Self-Supervised Representation Learning Mechanism) Using Neural Networks
[Kucukozer-Cavdar *et al*., 2021]	RF; k-NN; SVM
[Koch *et al*., 2021]	DBSCAN (Density-Based Clustering Non-Parametric Algorithm)

Source: authors

The challenges related to data quantity refer both to data scarcity [05][08][15][20][21][22][23][28][33][36] and to the difficulty in obtaining labeled data [28]. Data imbalance refers to the disproportional distribution between classes [18] [28] or to the underrepresentation of certain classes [28], which imposes limitations on generalization potential. As for data biases, they may be attributed to sample homogeneity [15][32][33][34], which also adds limitations to generalization, or to labeling bias [07][17][20][33].

As an example of a data quality-related challenge, Booth *et al*. [2022] assessed daily stress based on aggregated daily measures but were unable to model the aggregated temporal dynamics across different time periods during the day due to the low temporal resolution of the labels. Meanwhile, Pham *et al*. [2021] emphasize that the low precision in the dataset used suggests that factors such as ECG signal quality or emotion elicitation methods may impair learning effectiveness.

The category of modeling-related challenges encompasses model complexity [23][28] and multimodal data integration [05][15]. For instance, Henriquez *et al*. [2017] demonstrated that integrating heterogeneous sensors (e.g., ECG and video) may introduce signal noise, complicating feature extraction. This highlights the difficulties in developing generalizable models, particularly in contexts involving multiple data sources and diverse populations.

The category of technical and operational limitations identifies barriers to the practical implementation of machine learning systems, including computational infrastructure issues - such as power consumption [08][13], data transmission delays due to high latency [13], low sensor sensitivity [05], interoperability limitations [08], and imprecise location tracking [33] - as well as security concerns like IoT device vulnerabilities [13] and privacy issues [33]. Other reported limitations include challenges in analyzing physiological parameters that vary across individuals [24] and in morphological analysis [05].

For instance, the work by Akhtar *et al*. [2023] highlights that delays in cloud data transmission may compromise the effectiveness of real-time monitoring - a critical requirement for healthcare systems - thereby limiting the applicability of complex machine learning models in low-latency scenarios [Akhtar *et al*., 2023]. Similarly, Calatrava-Nicolás *et al*. [2021] emphasize that energy consumption, battery life, and device recharge time constitute critical challenges that must be addressed, as charging interruptions disrupt data acquisition in most systems.

The category of validation challenges addresses both the relationship between passively collected data and validation measures [05][08][11][23] , and the discrepancy between controlled and real-world environments [21][28]. For example, Henriquez *et al*. [2017] reported that heart rate variability (HRV) analyses yielded unsatisfactory results, showing considerable discrepancies compared to ECG-derived values, thus highlighting limitations in the correlation between different measurement methods.

Despite these challenges, numerous studies have demonstrated significant advances in the analysis of physiological and behavioral signals related to emotions and stress, proposing robust methods for classification and prediction. The effectiveness of these techniques varies according to context. For instance, neural networks show superior performance in subject-independent or emotion-independent tests, effectively capturing emotional context. In contrast, methods such as random forests prove more suitable for subject-dependent and emotion-dependent analyses [Pinto *et al*., 2020]. Furthermore, nonlinear features have shown advantages in physiological signal analysis, particularly for detecting negative affect [Pham *et al*., 2021]. Recurrence Quantification Analysis (RQA), a nonlinear technique, has demonstrated high accuracy in identifying negative emotions, underscoring the relevance of approaches that go beyond conventional linear methods.

The fusion of multiple emotional features also stands out as an effective strategy to enhance model accuracy. Jin *et al*. [2020] observed that combining different emotional audio features significantly improved accuracy in mental well-being analysis. The authors emphasize that attention-based models outperform direct connection fusion models, and that the integration of behavioral features also led to improvements in classification performance. This multimodal approach enables a richer and more precise representation of emotional states.

Another significant advance involves the development of methods capable of handling imbalanced data and small sample sizes. A notable example is the b-WELM (bias-added Weighted Extreme Learning Machine), which enhances generalization in scenarios with unequally represented classes [Chen *et al*., 2018].

In applications involving sequential data, such as continuous biomedical signals, time-based deep learning architectures (e.g., deep recurrent neural networks) have demonstrated superior performance, enhancing accuracy in affective state classification [Alam *et al*., 2019].

In summary, the development of machine learning-based solutions for complex domains such as well-being faces multiple challenges—ranging from fundamental data-related issues to technical and validation limitations. These findings underscore the need for ongoing research to overcome current constraints, particularly concerning well-being inference in naturalistic environments.

The findings indicate that current computational interfaces still privilege mental well-being, particularly through stress and affect recognition, while social well-being remains largely unexplored. This imbalance suggests that the field has not yet fully embraced the multidimensionality of well-being.

4.1.2 RQ2: Methods of Measuring User Well-Being

The second question aimed to identify the methods used to measure well-being. As discussed in the introduction, well-being is a multidimensional concept. Bradburn (1969) defines well-being as comprising two dimensions, separated by two sets of feelings: positive affects and negative affects. In this sense, well-being can be formed by both positive and negative emotional experiences. Additionally, well-being also encompasses life satisfaction, based on an individual's subjective cognitive evaluations. Measuring well-being is complex as it considers the inherent feelings of the individual.

Watson *et al*. [1988] and Bradburn [1969] are two authors who have dedicated efforts to evaluating and measuring well-

being by considering the two dimensions of affects, proposing subjective self-report instruments through the use of standardized questionnaires.

Building on self-report, various studies have focused on developing objective instruments for measuring affective dimensions, employing physiological or facial sensors. For example, Souza [2019] highlights that several sensors can be used to assess the emotional dimension of user well-being, including EDA sensors and GSR, which monitor changes in skin temperature and electrical conductivity; EEG sensors, which monitor brain activity through electrical signals of brain waves; ECG sensors, which capture heartbeats and variations in frequency (HRV); and the Facial Action Coding System (FACS).

Based on this, the methods of measuring well-being used in the reviewed studies were classified as either subjective (e.g., questionnaires, interviews) or objective (e.g., sensors). All studies employed objective methods, and 81% also used subjective methods.

Regarding objective methods, sensors that monitor users' physiological signals were initially classified as either commercial or homemade. Among the studies reviewed, 67% used commercial sensors while 42% used homemade sensors, meaning they built their own tools using low-cost sensors. Four studies employed both types of solutions.

The most commonly used sensors for measuring well-being were ECG, EDA, accelerometer, environmental sensors (such as ambient temperature, atmospheric pressure, humidity, sound, etc.), and PPG, as shown in Figure 9.

Among the studies that analyzed the mental dimension of well-being, 65% used ECG sensors and 42% used EDA sensors. Regarding physical well-being, 62% employed ECG sensors and 31% used EDA sensors. Finally, in the social dimension, one study used ECG sensors, and no studies employed EDA sensors.

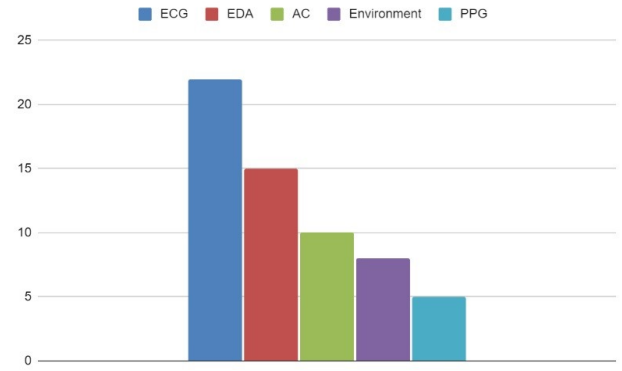


Figure 9. Number of articles, according to sensors used to measure well-being.

Source: authors.

Different signal processing and classification techniques were employed to assess well-being from the sensors' data. An example of these techniques can be found in Pinto *et al*. [2020], who analyzed which signal or combination of signals best describes an emotional response. Their work was divided into three stages: (1) signal preprocessing; (2) feature extraction; (3) classification using random forest and neural networks. In the preprocessing stage, an ECG signal was filtered using a Butterworth low-pass filter with a cut-off frequency of 40 Hz. The EDA signal was filtered with a Butterworth low-pass filter with a cutoff frequency of 5 Hz. To extract features from the collected physiological data, Neurokit was used, and correlated features were selected. The correlation threshold method was employed to reduce data redundancy. Examples of features extracted from the ECG include: heart rate, RR intervals, high-frequency heart rate variability, low-frequency heart rate variability, and T waves. From the EDA signal: Skin Conductance Response (SCR) indices. The selected features were used as inputs for machine learning methods: random forest and neural networks (multilayer perceptron with backpropagation).

Regarding subjective methods, the most commonly used questionnaires to assess emotional state and measure well-being were the Positive and Negative Affect Schedule (PANAS) [2][7][8][14][16][36], a tool created by Watson *et al*. [1988] to investigate users' positive and negative affective states, and the Self-Assessment Manikin (SAM) [19][20][24][26][30], a non-verbal pictorial assessment technique to measure pleasure, arousal, and dominance associated with a person's affective reaction to various stimuli.

The predominance of physiological sensing demonstrates the technological maturity of these approaches, with subjective self-reports often used as complementary measures.

4.1.3 RQ3: Interventions

The third question focused on describing how the solution generated interventions and which interventions were implemented. As previously presented in Figure 8, only 39% of the proposed solutions involved some interaction with the user, and these interactions did not always lead to interventions in the user's well-being. Among the solutions that implemented interventions in user well-being (10 studies), 8 proposed a recommendation system (suggesting physical activity practices, healthy eating habits, and other behavioral changes), while 2 developed conversational interfaces aimed at improving physical and mental well-being. These findings align with the observations of El Kamali *et al*. [2020], who identified few conversational agent approaches employed in well-being-focused solutions.

As indicated in Table 7, the majority of interventions were focused on enhancing mental and/or physical dimensions of well-being. These interventions predominantly involved text messages that provided recommendations for relaxation activities, dietary modifications, and physical activity.

The interventions were classified into types, with the most frequent being: physical activity (6 instances); relaxation activities (5 instances); healthy eating habits (4 instances); social activities (4 instances); reduction of harmful health habits (2 instances).

For example, Honka *et al*. [2022] introduced the With-Me HRS prototype, which evaluates individuals' needs for behavioral change across 14 domains related to well-being and a healthy lifestyle: physical activity, dietary habits, sleep, smoking, alcohol consumption, stress management, work-life balance, social relationships, emotional well-being, mental health, overall physical health, self-care, sleep habits, and time management.

The With-Me HRS system assesses behavioral change

needs across various areas related to well-being and a healthy lifestyle, including increasing physical activity, improving dietary habits, enhancing sleep patterns, reducing tobacco consumption, decreasing alcohol intake, managing stress, and cultivating social relationships, among others. The With-Me HRS framework consists of three main components: a personal profile, an intervention library, and a recommendation mechanism. The personal profile is created by integrating data from multiple sources, such as online questionnaires, lifestyle assessments based on physiological monitoring (using the Firstbeat Lifestyle Assessment), and other behavioral evaluation tools.

The intervention library was structured with over 100 activities aimed at promoting behavioral changes in the mentioned domains. Examples of activities include reading online articles about stress symptoms and management practices, quizzes to assess alcohol consumption patterns, establishing sleep habits, maintaining a food diary, restructuring the physical environment by keeping fruits visible and vegetables easily accessible at home, among other strategies.

Intervention rules were integrated into the intervention library for the specified resources grounded on health monitoring through heart rate variability, as assessed by Firstbeat Lifestyle Assessment, alongside self-reported well-being. The recommendation mechanism allows for retrieving behavioral change activity recommendations and participant readiness for change from the intervention library, which are then presented in the interface to users. Examples of recommendations include: ”Read an online article about the symptoms of stress and good practices for stress management”, ”Take a quiz for evaluating your alcohol consumption patterns”, ”Get an exercise buddy”, ”Make a realistic list of work tasks for the upcoming work day”, ”Keep a diary about eating habits for three days”, ”Keep fruits in sight and vegetables easily accessible at home”, ”Wake up at the same time every day” and ”Practice mindfulness skills with Oiva exercises”.

Interventions remain limited to simple recommendations, with few adaptive or conversational systems. This highlights a gap between monitoring capacity and the ability to deliver personalized, effective, and context-aware interventions.

Table 7. Relationship between well-being dimension, sensors, and type of intervention

Author	Well-being dimension	Sensors	Type of solution	Type of intervention
[Meegahapola and Gatica-Perez, 2020]	Physical; Menta	ECG; Accelerometer	Recommendation system	Text messages recommending healthy eating habits, physical activity, relaxation activities, social activities, and reduction of health-damaging habits (smoking and alcohol consumption).
[Lacuesta *et al*., 2017]	Mental	ECG	Recommendation system	Report classifying visited residential areas according to user's stress levels.
[Kasuya *et al*., 2017]	Physical; Social	GPS; Accelerometer	Recommendation system	Text messages recommending physical activity, relaxation activities, and social activities.
[Henriquez *et al*., 2017]	Physical; Mental	FACs	Recommendation system	Text messages recommending healthy eating habits, physical activity, and reduction of health-damaging habits (smoking and alcohol consumption).
[Do *et al*., 2020]	Physical; Mental	FACs; Microphone	Conversational interface	Clinical screening interviews (through audio and text) for cognitive assessment, mood detection, loneliness assessment, and pain evaluation. Based on the monitored data, it performs social activities (such as playing music, telling jokes), reads news, provides weather forecasts, and plays games.
[Pham *et al*., 2021]	Mental	ECG; Microphone	Conversational interface	Mood detection (through audio and text). Based on the monitored data, performs cognitive activities (e.g., math games).
[Khattak *et al*., 2016]	Physical; Mental; Social	ECG; EEG; GPS; Accelerometer; Camera, Gyroscope, Bluetooth and Microphone	Recommendation system	Text messages recommending healthy eating habits, physical activity, and social activities
[Kraaij *et al*., 2020]	Physical; Mental	ECG; EDA; FACs	Recommendation system	Text messages recommending healthy eating habits, physical activity, and relaxation activities
[Kucukozer-Cavdar *et al*., 2021]	Physical	GPS; Accelerometer	Recommendation system	Text messages recommending physical activity and relaxation activities
[Koch *et al*., 2021]	Mental	GPS; Accelerometer	Recommendation system	Audio messages recommending relaxation activities (mindfulness or a music playlist previously chosen by the user)

Source: authors

5 Conclusion and future works

In this article, a systematic mapping was conducted to identify and investigate the state of the art in computational interfaces that adapt according to the user's context, with a focus on their well-being. A total of 36 articles relevant to the research questions were identified.

The contributions of this mapping reveal that mental state is the primary focus of studies on user well-being involving computational solutions, with a strong emphasis on health, particularly affective states and stress. The most common stimuli used to assess well-being are activities in the user's natural environment, followed by visual stimuli.

Most studies did not focus on interventions aimed at improving user well-being but rather on validating the subjectively reported state of well-being through sensor-based metrics, developed and trained using artificial intelligence algorithms.

Current research is focused on validating and predicting key methods for assessing user well-being. The most commonly employed techniques are based on neural network algorithms, with less emphasis on studies focused on well-being interventions. This represents a significant gap, highlighting the need for further exploration into both computational solutions and well-being interventions. This finding is consistent with Oyebode et al. (2023), which found that the majority of reviewed studies (78%) did not evaluate the effectiveness of the solutions to determine whether the proposed interventions were truly appropriate for users. Additionally, none of the reviewed studies utilized interface adaptation itself as a well-being stimulus, meaning that no research implemented changes to the interface to modify the user's state of well-being.

Slightly over one-third of the studies involved interventions, most of them focusing on recommendations to promote relaxation, physical activity, and healthy eating habits. User-interface interaction predominantly occurred through text messages displayed on the interface, with audio being less frequently used.

In terms of measurement, all articles employed objective instruments, with ECG and EDA sensors being the most common. Most studies also used subjective instruments, with PANAS and SAM questionnaires being the most frequently used. The systematic mapping of these studies indicates that the combined use of sensors provides more robust and precise results in assessing well-being.

Given these contributions, future work should consider expanding searches within specialized health databases and incorporating additional descriptors into the search string, such as "affective computing", as the term "affective" was frequently found in the abstracts of the reviewed papers.

This systematic review of recent research on adaptive computational interfaces for well-being interventions highlighted key trends in personalized, data-driven approaches. Current studies emphasize integrating wearable sensors, artificial intelligence, and multimodal feedback systems to monitor and enhance physical, mental, and social well-being. A common trend is the application of machine learning models and deep learning architectures for well-being assessment, leveraging physiological signals, behavioral patterns, and environmental factors.

Despite significant advancements, several limitations persist. One of the most recurrent challenges is the quality, quantity, imbalance, and bias of the data, which directly affect model robustness and generalizability. Algorithmic complexities and the integration of multimodal data further complicate model development, while operational barriers, such as computational infrastructure, sensor reliability, and privacy concerns, pose additional constraints. Moreover, real-world validation and consistency across different measurement methods remain critical challenges for practical deployment. To address these gaps, future research should prioritize more diverse and inclusive user samples, develop standardized evaluation frameworks, and refine adaptive interventions that dynamically cater to individual needs.

Advancements in human-centered AI and the integration of emerging technologies, such as augmented reality and neurofeedback, could further enhance personalized well-being solutions. Additionally, improving data collection methodologies, refining algorithmic models to better capture contextual influences, and conducting long-term validation studies will be crucial steps toward more effective, scalable, and ethically sound well-being interventions.

These findings highlight the following priorities for future research on adaptive systems designed to promote well-being:

- Expand the scope of well-being studies beyond the mental dimension to encompass physical, social, and other domains that contribute to overall human well-being.
- Design adaptive and context-sensitive interventions that go beyond mere monitoring systems.
- Increase ecological validity by conducting longitudinal studies on the natural environment.
- Address data challenges by improving labeling, reducing bias, and creating open multimodal datasets.
- Standardize evaluation frameworks and share benchmarks to improve comparability across studies.
- Explore emerging technologies (e.g., augmented reality, neurofeedback, conversational agents) for richer user engagement.
- Advance human-centered AI approaches, including explainability, transparency, and ethical safeguards.

Within the Brazilian context, these findings acquire particular relevance when considered in light of national research agendas that seek to articulate local challenges with global advances in Human-Computer Interaction. The GranDIHC-BR 2025–2035 initiative [Pereira *et al*., 2024] outlines seven major challenges for the coming decade, which provide a prospective and situated framework for discussing adaptive systems for well-being. Specifically, the discussion intersects with GC4 by highlighting the importance of sociocultural contextualization in the design of adaptive systems, ensuring inclusivity and cultural sustainability in a country marked by profound diversity [Neris *et al*., 2024]. It also converges with GC6 by addressing the ethical and algorithmic challenges of artificial intelligence in Human-Data Interaction, underscoring the need for transparency and fairness in well-being applications, and reinforcing the significance of computational practices aligned with human values and the mitigation of algorithmic biases [Duarte *et al*., 2024]. Finally, the emphasis on emerging and hybrid technologies is consistent

with GC7, which advocates for an ecosystemic perspective capable of fostering meaningful, ethical, and sustainable interactions between humans and adaptive technologies [Zaina *et al*., 2024]. In this sense, the Brazilian agenda expands the debate by stressing that the development of adaptive systems and context-sensitive interfaces must also incorporate environmental, economic, and sociocultural concerns, always respecting users' lived realities. Together, these connections demonstrate that future advances in adaptive systems for well-being should not only pursue technical innovation, but also integrate ethical, cultural, and social dimensions, thereby contributing to a more inclusive and responsible trajectory for Human-Computer Interaction in Brazil.

6 Limitations

The primary limitation of this study relates to the scope of its findings due to the inclusion and exclusion criteria adopted. The selection of articles was restricted to four major academic databases—IEEE Computer Society, ACM Digital Library, Springer Link, and PubMed—potentially omitting relevant research published in other sources. Additionally, the linguistic scope was limited to English, which may have led to the exclusion of studies offering valuable insights, thus affecting the geographical representativeness of the results.

Moreover, the process of defining the search string, while designed to be broad and inclusive, may have introduced a selection bias. The choice of specific terms inevitably influenced the retrieval of studies, potentially overlooking relevant research that employed alternative terminology. Furthermore, the inclusion and exclusion process was conducted by a single researcher, which may have introduced potential bias in the selection of studies. To mitigate this limitation, the selected studies were subsequently reviewed and validated through team discussions, ensuring greater accuracy and reducing subjectivity.

Future research on systematic mapping in this field should consider expanding searches within specialized health databases and incorporating additional descriptors into the search string, such as 'affective computing,' since the term 'affective' frequently appeared in the abstracts of the reviewed papers.

While these constraints might have excluded significant works in the field, they do not diminish the study's capacity to identify key trends in research on adaptive interfaces to promote well-being. Instead, the findings provide a rich sample of the challenges in this domain, contributing to a broader understanding of its research landscape.

Declarations

Authors' Contributions

AA: Conceptualization. AA and FLO: Investigation, Formal Analysis, and Writing Original Draft. FLO and VN: Methodology, Review and Editing. VN: Supervision. All authors read and approved the final manuscript.

Competing interests

The authors report there are no competing interests to declare.

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Availability of data and materials

The materials supporting this study are available in the Appendix.

Disclosure statement

The authors used ChatGPT and Grammarly to assist in translating the manuscript from Portuguese into English; all content was reviewed and validated by the authors.

References

Akhtar, M. M., Shatat, A. S. A., Al-Hashimi, M., Zamani, A. S., Rizwanullah, M., Mohamed, S. S. I., and Ayub, R. (2023). Mapreduce with deep learning framework for student health monitoring system using iot technology for big data. *Journal of Grid Computing*, 21(4):67. DOI: 10.1007/s10723-023-09690-x.

Alam, M. G. R., Abedin, S. F., Moon, S. I., Talukder, A., and Hong, C. S. (2019). Healthcare iot-based affective state mining using a deep convolutional neural network. *IEEE Access*, 7:75189–75202. DOI: 10.1109/ACCESS.2019.2919995.

Ali, K., Shah, S., and Hughes, C. E. (2023). In-the-wild affect analysis of children with asd using heart rate. *Sensors*, 23(14):6572. DOI: 10.3390/s23146572.

Arabian, H., Abdulbaki Alshirbaji, T., Schmid, R., Wagner-Hartl, V., Chase, J. G., and Moeller, K. (2023). Harnessing wearable devices for emotional intelligence: Therapeutic applications in digital health. *Sensors*, 23(19):8092. DOI: 10.3390/s23198092.

Aristizabal, S., Byun, K., Wood, N., Mullan, A. F., Porter, P. M., Campanella, C., Jamrozik, A., Nenadic, I. Z., and Bauer, B. A. (2021). The feasibility of wearable and self-report stress detection measures in a semi-controlled lab environment. *IEEE Access*, 9:102053–102068. DOI: 10.1109/ACCESS.2021.3097038.

Arquissandas, P., Lamas, D. R., and Oliveira, J. (2023). Moving from vr into ar using bio-cybernetic loops and physiological sensory devices for intervention on anxiety disorders. *Virtual Reality*, 27(1):233–243. DOI: 10.1007/s10055-021-00549-8.

Birenboim, A., Ben-Nun Bloom, P., Levit, H., and Omer, I. (2021). The study of walking, walkability and wellbeing in immersive virtual environments. *International journal*

of environmental research and public health, 18(2):364. DOI: 10.3390/ijerph18020364.

Booth, B. M., Vrzakova, H., Mattingly, S. M., Martinez, G. J., Faust, L., and D'Mello, S. K. (2022). Toward robust stress prediction in the age of wearables: Modeling perceived stress in a longitudinal study with information workers. *IEEE Transactions on Affective Computing*, 13(4):2201–2217. DOI: 10.1109/TAFFC.2022.3188006.

Bradburn, N. M. (1969). The structure of psychological well-being.. DOI: 10.1037/t10756-000.

Brdnik, S., Heričko, T., and Šumak, B. (2022). Intelligent user interfaces and their evaluation: a systematic mapping study. *Sensors*, 22(15):5830. DOI: 10.3390/s22155830.

Calatrava-Nicolás, F. M., Gutiérrez-Maestro, E., Bautista-Salinas, D., Ortiz, F. J., González, J. R., Vera-Repullo, J. A., Jiménez-Buendía, M., Méndez, I., Ruiz-Esteban, C., and Mozos, O. M. (2021). Robotic-based well-being monitoring and coaching system for the elderly in their daily activities. *Sensors*, 21(20):6865. DOI: 10.3390/s21206865.

Carrera-Rivera, A., Larrinaga, F., Lasa, G., Reguera-Bakhache, D., and Unamuno, G. (2025). From past to present: Human–machine interfaces evolve toward adaptivity. In Sayago, S., Sendín, M., and Teixidó, M., editors, *Inclusive Smart Cities and Digital Health*. Springer, Cham. DOI: 10.1007/978-3-031-71697-3_7.

Chen, Y., Hu, C., Hu, B., Hu, L., Yu, H., and Miao, C. (2018). Inferring cognitive wellness from motor patterns. *IEEE Transactions on Knowledge and Data Engineering*, 30(12):2340–2353. DOI: 10.1109/TKDE.2018.2820024.

Cornet, V. P. and Holden, R. J. (2018). Systematic review of smartphone-based passive sensing for health and wellbeing. *Journal of biomedical informatics*, 77:120–132. DOI: 10.1016/j.jbi.2017.12.008.

Dissanayake, V., Tang, V., Elvitigala, D. S., Wen, E., Wu, M., and Nanayakkara, S. (2022). Troi: Towards understanding users perspectives to mobile automatic emotion recognition system in their natural setting. *Proceedings of the ACM on Human-Computer Interaction*, 6(MHCI):1–22. DOI: 10.1145/3546738.

Do, H. M., Sheng, W., Harrington, E. E., and Bishop, A. J. (2020). Clinical screening interview using a social robot for geriatric care. *IEEE Transactions on Automation Science and Engineering*, 18(3):1229–1242. DOI: 10.1109/TASE.2020.2999203.

Duarte, E. F., Toledo Palomino, P., Pontual Falcão, T., Porto, G. L. P. M. B., Portela, C. d. S., Ribeiro, D. F., Nascimento, A., Costa Aguiar, Y. P., Souza, M., Moutin Segoria Gasparotto, A., *et al*. (2024). Grandihc-br 2025-2035-gc6: Implications of artificial intelligence in hci: A discussion on paradigms ethics and diversity equity and inclusion. In *Proceedings of the XXIII Brazilian Symposium on Human Factors in Computing Systems*, pages 1–19. DOI: 10.1145/3702038.3702059.

El Kamali, M., Angelini, L., Caon, M., Carrino, F., Röcke, C., Guye, S., Rizzo, G., Mastropietro, A., Sykora, M., Elayan, S., *et al*. (2020). Virtual coaches for older adults' wellbeing: A systematic review. *Ieee Access*, 8:101884–101902. DOI: 10.1109/ACCESS.2020.2996404.

Fischer, G. (2023). Adaptive and adaptable systems: Differentiating and integrating ai and eud. In *International Symposium on End User Development*, pages 3–18. Springer. DOI: 10.1007/978-3-031-34433-6_1.

Galindo, J. A., Dupuy-Chessa, S., and Céret, É. (2017). Toward a ui adaptation approach driven by user emotions. In *ACHI'2017-The Tenth International Conference on Advances in Computer-Human Interactions*, pages 12–17. IARIA. Available at: `https://personales.upv.es/thinkmind/dl/conferences/achi/achi_2017/achi_2017_1_30_20048.pdf`.

Gonçalves, T. G., Kolski, C., de Oliveira, K. M., Travassos, G. H., and Strugeon, E. G.-L. (2019). A systematic literature review on intelligent user interfaces: preliminary results. In *Adjunct Proceedings of the 31st Conference on l'Interaction Homme-Machine*, pages 1–8. DOI: 10.1145/3366551.3370344.

Heikkilä, P., Honka, A., Kaasinen, E., and Väänänen, K. (2021). Quantified factory worker: field study of a web application supporting work well-being and productivity. *Cognition, Technology & Work*, 23(4):831–846. DOI: 10.1007/s10111-021-00671-2.

Henriquez, P., Matuszewski, B. J., Andreu-Cabedo, Y., Bastiani, L., Colantonio, S., Coppini, G., D'Acunto, M., Favilla, R., Germanese, D., Giorgi, D., *et al*. (2017). Mirror mirror on the wall... an unobtrusive intelligent multisensory mirror for well-being status self-assessment and visualization. *IEEE transactions on multimedia*, 19(7):1467–1481. DOI: 10.1109/TMM.2017.2666545.

Hinterberger, T. and Fürnrohr, E. (2016). The sensorium: Psychophysiological evaluation of responses to a multimodal neurofeedback environment. *Applied Psychophysiology and Biofeedback*, 41:315–329. DOI: 10.1007/s10484-016-9332-2.

Honka, A. M., Nieminen, H., Similä, H., Kaartinen, J., and Van Gils, M. (2022). A comprehensive user modeling framework and a recommender system for personalizing well-being related behavior change interventions: Development and evaluation. *IEEE Access*, 10:116766–116783. DOI: 10.1109/ACCESS.2022.3218776.

Innocent, P. (1982). Towards self-adaptive interface systems. *International Journal of Man-Machine Studies*, 16(3):287–299. DOI: 10.1016/S0020-7373(82)80063-1.

Jiang, L., Gao, B., Gu, J., Chen, Y., Gao, Z., Ma, X., Kendrick, K. M., and Woo, W. L. (2018). Wearable long-term social sensing for mental wellbeing. *IEEE Sensors Journal*, 19(19):8532–8542. DOI: 10.1109/JSEN.2018.2877427.

Jin, J., Gao, B., Yang, S., Zhao, B., Luo, L., and Woo, W. L. (2020). Attention-block deep learning based features fusion in wearable social sensor for mental wellbeing evaluations. *Ieee Access*, 8:89258–89268. DOI: 10.1109/ACCESS.2020.2994124.

Kasuya, S., Zhou, X., Tago, K., Nishimura, S., and Jin, Q. (2017). Cyber-enabled well-being oriented daily living support based on personal data analysis. *IEEE Transactions on Emerging Topics in Computing*, 8(2):493–502. DOI: 10.1109/TETC.2017.2763966.

Khattak, A. M., Khan, W. A., Pervez, Z., Iqbal, F., and Lee, S. (2016). Towards a self adaptive system for social wellness. *Sensors*, 16(4):531. DOI: 10.3390/s16040531.

Kiefer, R. A. (2008). An integrative review of the concept of well-being. *Holistic nursing practice*, 22(5):244–252. DOI: 10.1097/01.HNP.0000334915.16186.b2.

Koch, K., Mishra, V., Liu, S., Berger, T., Fleisch, E., Kotz, D., and Wortmann, F. (2021). When do drivers interact with in-vehicle well-being interventions? an exploratory analysis of a longitudinal study on public roads. *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies*, 5(1):1–30. DOI: 10.1145/3448116.

Kraaij, W., Verberne, S., Koldijk, S., de Korte, E., van Dantzig, S., Sappelli, M., Shoaib, M., Bosems, S., Achterkamp, R., Bonomi, A., *et al*. (2020). Personalized support for well-being at work: an overview of the swell project. *User modeling and user-adapted interaction*, 30:413–446. DOI: 10.1007/s11257-019-09238-3.

Kucukozer-Cavdar, S., Taskaya-Temizel, T., Mehrotra, A., Musolesi, M., and Tino, P. (2021). Designing robust models for behaviour prediction using sparse data from mobile sensing: a case study of office workers' availability for well-being interventions. *ACM Transactions on Computing for Healthcare*, 2(4):1–33. DOI: 10.1145/3458753.

Lacuesta, R., Garcia, L., García-Magariño, I., and Lloret, J. (2017). System to recommend the best place to live based on wellness state of the user employing the heart rate variability. *IEEE Access*, 5:10594–10604. DOI: 10.1109/ACCESS.2017.2702107.

Li, B. and Sano, A. (2020). Extraction and interpretation of deep autoencoder-based temporal features from wearables for forecasting personalized mood, health, and stress. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 4(2):1–26. DOI: 10.1145/3397318.

Martinez, R., Salazar-Ramirez, A., Arruti, A., Irigoyen, E., Martin, J. I., and Muguerza, J. (2019). A self-paced relaxation response detection system based on galvanic skin response analysis. *IEEE Access*, 7:43730–43741. DOI: 10.1109/ACCESS.2019.2908445.

Maybury, M. (1998). Intelligent user interfaces: an introduction. In *Proceedings of the 4th international conference on Intelligent user interfaces*, pages 3–4. DOI: 10.1145/291080.291081.

Meegahapola, L. and Gatica-Perez, D. (2020). Smartphone sensing for the well-being of young adults: A review. *IEEE Access*, 9:3374–3399. DOI: 10.1109/ACCESS.2020.3045935.

Meza-Kubo, V., Morán, A. L., Carrillo, I., Galindo, G., and García-Canseco, E. (2016). Assessing the user experience of older adults using a neural network trained to recognize emotions from brain signals. *Journal of biomedical informatics*, 62:202–209. DOI: 10.1016/j.jbi.2016.07.004.

Naylor, M., Morrison, B., Ridout, B., and Campbell, A. (2019). Augmented experiences: investigating the feasibility of virtual reality as part of a workplace wellbeing intervention. *Interacting with Computers*, 31(5):507–523. DOI: 10.1093/iwc/iwz033.

Neris, V. P., Rosa, J. C. S., Maciel, C., Pereira, V. C., Galvão, V. F., and Arruda, I. L. (2024). Grandihc-br 2025-2035-gc4: Sociocultural aspects in human-computer interaction. In *Proceedings of the XXIII Brazilian Symposium on Human Factors in Computing Systems*, pages 1–14. DOI: 10.1145/3702038.3702057.

Norcio, A. F. and Stanley, J. (1989). Adaptive human-computer interfaces: A literature survey and perspective. *IEEE Transactions on Systems, Man, and cybernetics*, 19(2):399–408. DOI: 10.1109/21.31042.

Oyebode, O., Fowles, J., Steeves, D., and Orji, R. (2023). Machine learning techniques in adaptive and personalized systems for health and wellness. *International Journal of Human–Computer Interaction*, 39(9):1938–1962. DOI: 10.1080/10447318.2022.2089085.

Pereira, R., Darin, T., and Silveira, M. S. (2024). Grandihc-br: Grand research challenges in human-computer interaction in brazil for 2025-2035. In *Proceedings of the XXIII Brazilian Symposium on Human Factors in Computing Systems*, pages 1–24. DOI: 10.1145/3702038.3702061.

Petersen, K., Feldt, R., Mujtaba, S., and Mattsson, M. (2008). Systematic mapping studies in software engineering. In *12th international conference on evaluation and assessment in software engineering (EASE)*. BCS Learning & Development. DOI: 10.14236/ewic/EASE2008.8.

Pham, M., Do, H. M., Su, Z., Bishop, A., and Sheng, W. (2021). Negative emotion management using a smart shirt and a robot assistant. *IEEE Robotics and Automation Letters*, 6(2):4040–4047. DOI: 10.1109/LRA.2021.3067867.

Pinto, G., Carvalho, J. M., Barros, F., Soares, S. C., Pinho, A. J., and Brás, S. (2020). Multimodal emotion evaluation: A physiological model for cost-effective emotion classification. *Sensors*, 20(12):3510. DOI: 10.3390/s20123510.

Raheel, S. (2016). Improving the user experience using an intelligent adaptive user interface in mobile applications. In *2016 IEEE international multidisciplinary conference on engineering technology (IMCET)*, pages 64–68. IEEE. DOI: 10.1109/IMCET.2016.7777428.

Rinella, S., Massimino, S., Fallica, P. G., Giacobbe, A., Donato, N., Coco, M., Neri, G., Parenti, R., Perciavalle, V., and Conoci, S. (2022). Emotion recognition: Photoplethysmography and electrocardiography in comparison. *Biosensors*, 12(10):811. DOI: 10.3390/bios12100811.

Rodrigues, M. C. J., Postolache, O., and Cercas, F. (2023). The influence of stress noise and music stimulation on the autonomous nervous system. *IEEE Transactions on Instrumentation and Measurement*, 72:1–19. DOI: 10.1109/TIM.2023.3279881.

Sanchez, C., Cedillo, P., and Bermeo, A. (2017). A systematic mapping study for intelligent user interfaces-iui. In *2017 International Conference on Information Systems and Computer Science (INCISCOS)*, pages 361–368. IEEE. DOI: 10.1109/INCISCOS.2017.34.

Schlungbaum, E. (1997). Individual user interfaces and model-based user interface software tools. In *Proceedings of the 2nd international conference on Intelligent user interfaces*, pages 229–232. DOI: 10.1145/238218.238330.

Shishavan, H. H., Garza, J., Henning, R., Cherniack, M., Hirabayashi, L., Scott, E., and Kim, I. (2023). Continuous physiological signal measurement over 24-hour periods to assess the impact of work-related stress and workplace violence. *Applied ergonomics*, 108:103937. DOI: 10.1016/j.apergo.2022.103937.

Souza, I. E. d. (2019). Classificação de sinais fisiológicos para inferência do estado emocional de usuários. Available at: `https://repositorio.ufscar.br/handle/20.500.14289/12293`.

Strout, K. A. and Howard, E. P. (2012). The six dimensions of wellness and cognition in aging adults. *Journal of Holistic Nursing*, 30(3):195–204. DOI: 10.1177/0898010112440883.

Tong, C., Craner, M., Vegreville, M., and Lane, N. D. (2019). Tracking fatigue and health state in multiple sclerosis patients using connnected wellness devices. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 3(3):1–19. DOI: 10.1145/3351264.

Van Velsen, L., Van Der Geest, T., Klaassen, R., and Steehouder, M. (2008). User-centered evaluation of adaptive and adaptable systems: a literature review. *The knowledge engineering review*, 23(3):261–281. DOI: 10.1017/S0269888908001379.

Völkel, S. T., Schneegass, C., Eiband, M., and Buschek, D. (2020). What is" intelligent" in intelligent user interfaces? a meta-analysis of 25 years of iui. In *Proceedings of the 25th international conference on intelligent user interfaces*, pages 477–487. DOI: 10.1145/3377325.3377500.

Wang, Y. and Stroulia, E. (2003). Flexible interface matching for web-service discovery. In *Proceedings of the Fourth International Conference on Web Information Systems Engineering, 2003. WISE 2003.*, pages 147–156. IEEE. DOI: 10.1109/WISE.2003.1254478.

Watson, D., Clark, L. A., and Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the panas scales. *Journal of personality and social psychology*, 54(6):1063. DOI: 10.1037/0022-3514.54.6.1063.

Yang, S., Gao, B., Jiang, L., Jin, J., Gao, Z., Ma, X., and Woo, W. L. (2018). Iot structured long-term wearable social sensing for mental wellbeing. *IEEE Internet of Things Journal*, 6(2):3652–3662. DOI: 10.1109/JIOT.2018.2889966.

Yu, L., Chan, W. M., Zhao, Y., and Tsui, K.-L. (2018). Personalized health monitoring system of elderly wellness at the community level in hong kong. *IEEE Access*, 6:35558–35567. DOI: 10.1109/ACCESS.2018.2848936.

Zaina, L., Prates, R. O., Delabrida Silva, S. E., Choma, J., Valentim, N. M. C., Frigo, L. B., and Bicho, A. D. L. (2024). Grandihc-br 2025-2035-gc7: Interaction with emerging technologies: An ecosystem integrating humans technologies and contexts. In *Proceedings of the XXIII Brazilian Symposium on Human Factors in Computing Systems*, pages 1–21. DOI: 10.1145/3702038.3702060.

APPENDIX

Table 8. Articles selected in systematic mapping

ID	Authorship/ year of publication	Title
01	[Honka *et al*., 2022]	A Comprehensive User Modeling Framework and a Recommender System for Personalizing Well-Being Related Behavior Change Interventions: Development and Evaluation
02	[Naylor *et al*., 2019]	Augmented Experiences: Investigating the Feasibility of Virtual Reality as Part of a Workplace Wellbeing Intervention
03	[Lacuesta *et al*., 2017]	System to Recommend the Best Place to Live Based on Wellness State of the User Employing the Heart Rate Variability
04	[Kasuya *et al*., 2017]	Cyber-Enabled Well-Being Oriented Daily Living Support Based on Personal Data Analysis
05	[Henriquez *et al*., 2017]	Mirror Mirror on the Wall... An Unobtrusive Intelligent Multisensory Mirror for Well-Being Status Self-Assessment and Visualization
06	[Do *et al*., 2020]	Clinical Screening Interview Using a Social Robot for Geriatric Care
07	[Pham *et al*., 2021]	Negative Emotion Management Using a Smart Shirt and a Robot Assistant
08	[Calatrava-Nicolás *et al*., 2021]	Robotic-based well-being monitoring and coaching system for the elderly in their daily activities
09	[Hinterberger and Fürnrohr, 2016]	The sensorium: Psychophysiological evaluation of responses to a multimodal neurofeedback environment
10	[Khattak *et al*., 2016]	Towards a self adaptive system for social wellness
11	[Meza-Kubo *et al*., 2016]	Assessing the user experience of older adults using a neural network trained to recognize emotions from brain signals
12	[Heikkilä *et al*., 2021]	Quantified factory worker: field study of a web application supporting work well-being and productivity
13	[Akhtar *et al*., 2023]	MapReduce with Deep Learning Framework for Student Health Monitoring System using IoT Technology for Big Data
14	[Yang *et al*., 2018]	IoT Structured Long-Term Wearable Social Sensing for Mental Wellbeing
15	[Jin *et al*., 2020]	Attention-Block Deep Learning Based Features Fusion in Wearable Social Sensor for Mental Wellbeing Evaluations
16	[Jiang *et al*., 2018]	Wearable Long-Term Social Sensing for Mental Wellbeing
17	[Yu *et al*., 2018]	Personalized Health Monitoring System of Elderly Wellness at the Community Level in Hong Kong
18	[Chen *et al*., 2018]	Inferring Cognitive Wellness from Motor Patterns
19	[Alam *et al*., 2019]	Healthcare IoT-Based Affective State Mining Using a Deep Convolutional Neural Network
20	[Martinez *et al*., 2019]	A Self-Paced Relaxation Response Detection System Based on Galvanic Skin Response Analysis
21	[Aristizabal *et al*., 2021]	The Feasibility of Wearable and Self-Report Stress Detection Measures in a Semi-Controlled Lab Environment
22	[Booth *et al*., 2022]	Toward Robust Stress Prediction in the Age of Wearables: Modeling Perceived Stress in a Longitudinal Study With Information Workers
23	[Rodrigues *et al*., 2023]	The Influence of Stress Noise and Music Stimulation on the Autonomous Nervous System
24	[Rinella *et al*., 2022]	Emotion Recognition: Photoplethysmography and Electrocardiography in Comparison

Continuation of Table 8

ID	Authorship/ year of publication	Title
25	[Pinto *et al*., 2020]	Multimodal Emotion Evaluation: A Physiological Model for Cost-Effective Emotion Classification
26	[Arabian *et al*., 2023]	Harnessing Wearable Devices for Emotional Intelligence: Therapeutic Applications in Digital Health
27	[Shishavan *et al*., 2023]	Continuous physiological signal measurement over 24-hour periods to assess the impact of work-related stress and workplace violence
28	[Ali *et al*., 2023]	In-the-Wild Affect Analysis of Children with ASD Using Heart Rate
29	[Birenboim *et al*., 2021]	The study of walking, walkability and wellbeing in immersive virtual environments
30	[Arquissandas *et al*., 2023]	Moving from VR into AR using bio-cybernetic loops and physiological sensory devices for intervention on anxiety disorders
31	[Kraaij *et al*., 2020]	Personalized support for well-being at work: an overview of the SWELL project
32	[Li and Sano, 2020]	Extraction and interpretation of deep autoencoder-based temporal features from wear-ables for forecasting personalized mood, health, and stress
33	[Kucukozer-Cavdar *et al*., 2021]	Designing Robust Models for Behaviour Prediction Using Sparse Data from Mobile Sensing: A Case Study of Office Workers' Availability for Well-being Interventions
34	[Dissanayake *et al*., 2022]	Troi: Towards understanding users perspectives to mobile automatic emotion recogni-tion system in their natural setting
35	[Tong *et al*., 2019]	Tracking fatigue and health state in multiple sclerosis patients using connnected wellness devices
36	[Koch *et al*., 2021]	When do drivers interact with in-vehicle well-being interventions? An exploratory analysis of a longitudinal study on public roads

Source: authors