Toward Human-centered Artificial Intelligence for Users' Digital Well-being: Systematic Review, Synthesis, and Future Directions

Youngsoo Shin

Submitted to: JMIR Human Factors
on: December 02, 2024

Table of Contents

Toward Human-centered Artificial Intelligence for Users' Digital Well-being: Systematic Review, Synthesis, and Future Directions

Youngsoo Shin[1] PhD

[1]Seidenberg School of Computer Science and Information Systems Pace University West New York US

Corresponding Author:
Youngsoo Shin PhD
Seidenberg School of Computer Science and Information Systems
Pace University
1120
15 Beekman Street
West New York
US

Abstract

Background: As Information and Communication Technologies (ICTs) and Artificial Intelligence (AI) become deeply integrated into daily life, the focus on users' digital well-being has grown across academic and industrial fields. However, fragmented perspectives and approaches to digital well-being in AI-powered systems hinder a holistic understanding, leaving researchers and practitioners struggling to design truly human-centered AI systems.

Objective: This paper aims to address the fragmentation by synthesizing diverse perspectives and approaches to digital well-being through a systematic literature review. Using the Stimulus-Organism-Response (SOR) framework as a guiding lens, the study seeks to conceptualize a comprehensive model for designing human-centered AI systems that enhance digital well-being.

Methods: A systematic review of 240 multidisciplinary publications was conducted to explore the intersection of AI, digital well-being, and human-centered design. The analysis involved identifying key themes, frameworks, and approaches, with the SOR model serving as an overarching perspective to organize findings and inform model development.

Results: The review resulted in the Human-Centered AI for Digital Well-Being (HCAI-DW) model, a conceptual framework consolidating current knowledge on designing AI systems that support digital well-being and influence human behavior positively. The proposed model integrates insights from cross-disciplinary research, providing a structured understanding of how stimuli (AI system features) affect users' internal states (perceptions, emotions) and lead to behavioral responses and changes. Additionally, the paper highlights emerging challenges and opportunities, including ethical considerations, scalability, and practical guidelines for applying the model in long-term research and practice.

Conclusions: This study contributes to advancing the field by presenting an overarching framework for fostering digital well-being through human-centered AI systems. By addressing gaps in the fragmented literature and proposing a unifying model, the findings offer actionable insights for researchers and practitioners. The HCAI-DW model serves as a foundation for future exploration and practical application in creating intelligent computing systems that improve users' digital well-being in everyday life.

(JMIR Preprints 02/12/2024:69533)
DOI: https://doi.org/10.2196/preprints.69533

✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**
Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v
Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Original Manuscript

Original Paper

Youngsoo Shin, PhD
Seidenberg School of Computer Science and Information Systems, Pace University, New York City, New York, United States

Corresponding Author:
Youngsoo Shin, PhD
Seidenberg School of Computer Science and Information Systems
Pace University
Room 1120
15 Beekman Street
New York City
10038 New York
United States
Phone: +1 (212) 346 1888
Email: yshin@pace.edu

Toward Human-centered Artificial Intelligence for Users’ Digital Well-being: Systematic Review, Synthesis, and Future Directions

Abstract

Background: As Information and Communication Technologies (ICTs) and Artificial Intelligence (AI) become deeply integrated into daily life, the focus on users’ digital well-being has grown across academic and industrial fields. However, fragmented perspectives and approaches to digital well-being in AI-powered systems hinder a holistic understanding, leaving researchers and practitioners struggling to design truly human-centered AI systems.
Objective: This paper aims to address the fragmentation by synthesizing diverse perspectives and approaches to digital well-being through a systematic literature review. Using the Stimulus-Organism-Response (SOR) framework as a guiding lens, the study seeks to conceptualize a comprehensive model for designing human-centered AI systems that enhance digital well-being.
Methods: A systematic review of 240 multidisciplinary publications was conducted to explore the intersection of AI, digital well-being, and human-centered design. The analysis involved identifying key themes, frameworks, and approaches, with the SOR model serving as an overarching perspective to organize findings and inform model development.
Results: The review resulted in the Human-Centered AI for Digital Well-Being (HCAI-DW) model, a conceptual framework consolidating current knowledge on designing AI systems that support digital well-being and influence human behavior positively. The proposed model integrates insights from cross-disciplinary research, providing a structured understanding of how stimuli (AI system features) affect users’ internal states (perceptions, emotions) and lead to behavioral responses and changes. Additionally, the paper highlights emerging challenges and opportunities, including ethical considerations, scalability, and practical guidelines for applying the model in long-term research and practice.
Conclusions: This study contributes to advancing the field by presenting an overarching framework for fostering digital well-being through human-centered AI systems. By addressing gaps in the fragmented literature and proposing a unifying model, the findings offer actionable insights for researchers and practitioners. The HCAI-DW model serves as a foundation for future exploration and practical application in creating intelligent computing systems that improve users' digital well-being

in everyday life.

Keywords: digital well-being; human-centered computing; artificial intelligence; human-AI interaction; user experience; systematic literature review

Introduction

Digital well-being is a concept that describes the impact of Information and Communication Technologies (ICTs) on people's physical and mental well-being in general[1-3]. Researchers and practitioners in many relevant fields, including computer science, health care, Human-computer Interaction (HCI), psychology, cognitive science, and data science, have emphasized that there are plenty of opportunities to leverage everyday ICTs in users' daily human-computer interactions [4-14]. In this regard, everyday interactive and intelligent computing systems have been developed and investigated mainly with a focus on peoples' higher level of involvement in technology used to enhance their well-being and behavioral design [2, 15].

Existing literature has provided diverse methods and approaches for building computing systems that support users' daily quality-of-life by promoting users' positive attitudinal and behavioral changes [16]. For the past decade, the trend of increasing computing systems' complexity and interactivity has stimulated the introduction of a variety of Artificial Intelligence (AI) technologies (e.g., chatbots, voice assistants, self-driving vehicles, or recommendation systems) that have penetrated far into people's everyday lives [17, 18]. The application areas of these interactive intelligent systems include (1) consumer applications such as recommendation systems and social media platforms, (2) consequential applications in medical, legal, environmental, or financial systems, and (3) life-critical applications like those in cars, airplanes, or military systems [19]. Furthermore, the recent COVID-19 pandemic has accelerated the use and adoption of these AI-powered intelligent systems in people's lifestyles [20]. For example, the social distancing restrictions in everyday life during the pandemic have increased the demand for AI-powered services and non-contact operations such as driverless delivery services, pre-entry wellness checking systems, or autonomous cleaning solutions [21, 22].

On the other hands, several studies on digital well-being have pointed out negative aspects of previous approaches and perspectives that maximize users' engagement with these computing systems by attracting their attention and encouraging them to interact with the systems more frequently [1, 23-26]. In this regard, large global technology companies, such as Google, Apple, Microsoft, and Meta have reframed the meaning of digital well-being and have incorporated digital well-being into their business models. They have introduced various design and system features to help users manage their interactions with these computing systems and address users' challenges in terms of being overloaded and distracted by the systems [27]. Many of these features have been developed as Personal Informatics Tools (PITs) or Digital Self-control Tools (DSCTs). With an emphasis on instant and short-term well-being enhancing intervention, these tools have mainly allowed users to monitor and reflect on their technology use with interactive timers, usage dashboards, or lock-out features [16, 25].

The concept of digital well-being has interpreted in a broad sense among relevant fields with a strong consideration of daily HCI and recent Human-AI Interaction (HAII) [28]. However, as aforementioned, several researchers and practitioners have also construed in a limited sense of the term by sharing a consensus that "excessive" and "frequent" use of systems could result in physical or mental health problems for users [11, 29-34]. Despite this perspective gap, there is still a lack of studies that systematically reframe the concept of digital well-being with AI-powered computing systems. Further, the varying approaches developed in the related disciplines tend to focus on domain/device/context-specific and fragmented aspects of human experience and interactions with computing systems, which can be limiting for researchers and practitioners as they search for a holistic understanding of digital well-being in daily HCIs and HAIIs [2, 15, 25, 35, 36].

In response, this paper sees the value in consolidating diverse but scattered initiatives regarding designing Human-centered AI (HCAI) systems for users' digital well-being to support effective implementation by researchers and practitioners. More specifically, this paper addresses the research question as follows: "*How can existing research on digital well-being with intelligent computing systems be reframed and synthesized toward an overarching model for human-centered AI*?" As part of the effort to develop such a cumulative body of knowledge, this paper conducts a multidisciplinary systematic literature review on intelligent computing systems for users' daily digital well-being with a consideration of *user*- and *human*-centered perspectives. The findings from the review serves as a conceptual foundation for the development of an overarching model: Human-centered AI for Digital Well-being (HCAI-DW) model. The results from this consolidation are also expected to enrich the current understanding of digital well-being in daily HCIs for further implementation of designing human-centered computing systems.

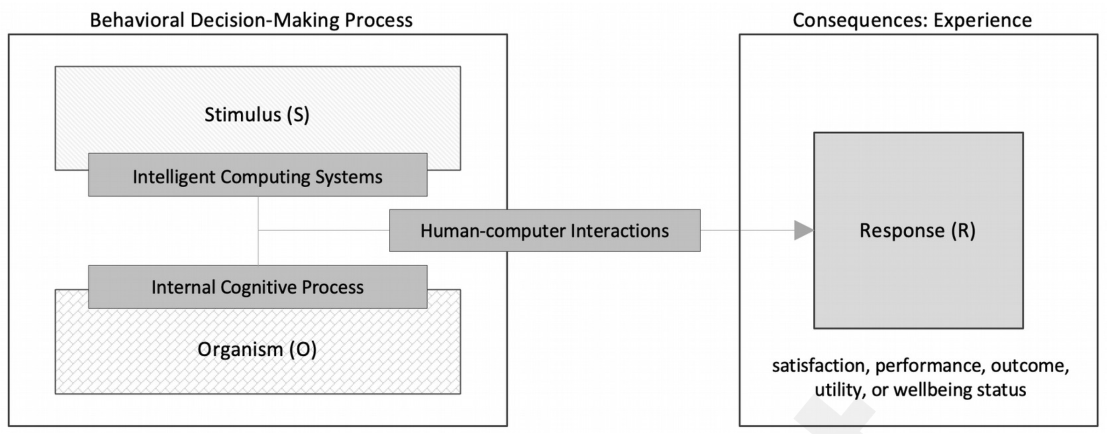
Systematic Literature Review

Theoretical Framework: The Stimulus-Organism-Response Model

To address the current knowledge gaps, this study developed an initial conceptual model of human-centered computing for digital well-being. In this process, this paper incorporated the Stimulus-Organism-Response (SOR) model. According to the SOR model [37, 38], an individual's responses to a stimulus is the result of a behavioral decision-making process that reflects interplay between internal aspects (e.g., preference, personality, ability, motivation, etc.) and external aspects of the specific context (e.g., time, money, weather, etc.). The SOR model states that either context or environment could be understood as a stimulus (S), which consists of a set of designed or non-designed interactions that causes an internal cognitive process in individuals (O) and produces a response (R) [39, 40].

The SOR model has allowed researchers and practitioners in various fields to investigate how humans interact with non-human objects in a broad and comprehensive way [39]. In this regard, many have incorporated the model because of its broader range of possibilities for human behavior and objects and its structured way of focusing on behavioral mechanisms instead of behavioral consequences (e.g., satisfaction, performance, outcome, utility, or increased well-being status). For this reason, this paper seeks to bridge the existing perspective gaps by utilizing the basic SOR model, with complementary points of view for digital well-being and human-centered AI computing systems.

Figure 1. Overarching Viewpoint of Digital Well-being with Intelligent Computing Systems.

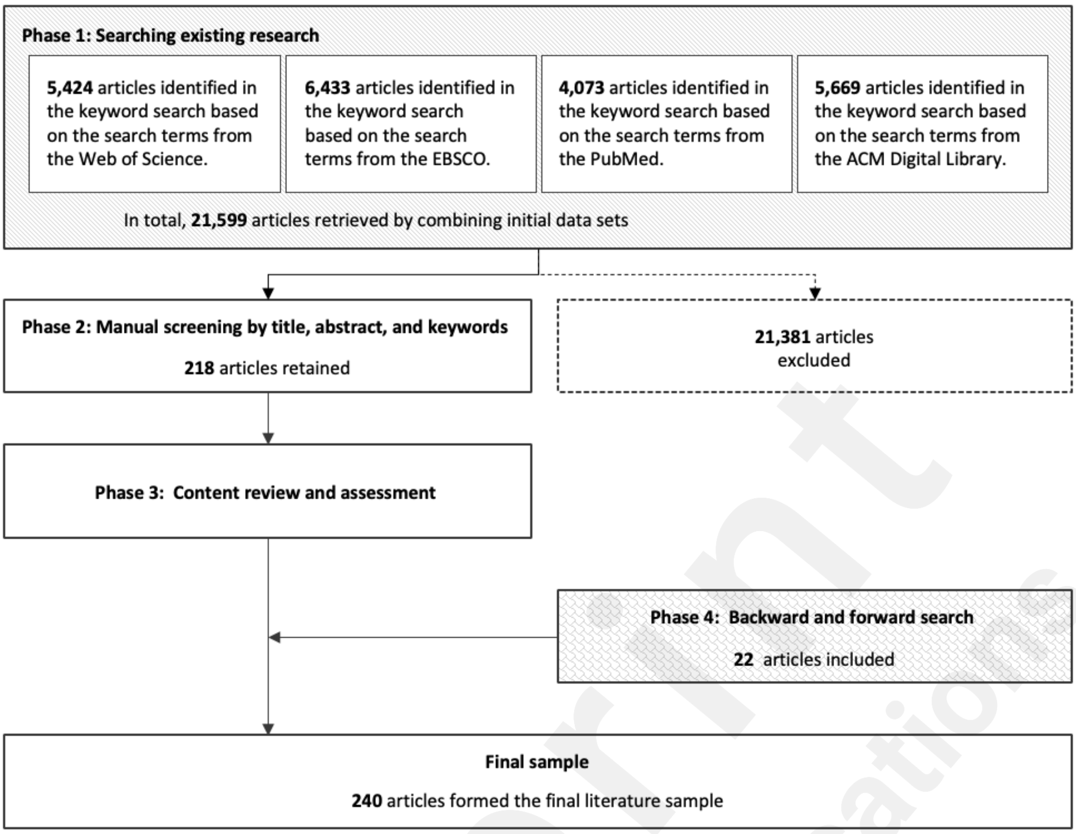


Through incorporating the SOR model as an initial viewpoint, it is expected that this study can investigate multi-layered aspects of digital well-being with intelligent computing systems (Figure 1). Most previous perspectives on digital well-being in relevant fields mainly paid attention to the "consequences" of experiences (e.g., satisfaction, performance, outcome, utility, etc.), instead of focusing on the different ways people make a behavioral decision and their divergent experiential processes with intelligent systems and technologies. Although researchers and practitioners should consider behavioral decision-making mechanisms as well as a specific behavioral result targeted by designed interactions, including interface and system features, a systematic understanding of the multi-dimensional aspects of the behavioral decision-making process within the research boundary of design for digital well-being with intelligent computing systems is still lacking. Therefore, within the perspective of the SOR model, this study concentrates on individuals' behavioral decision-making mechanisms as a core concept for the unified conceptualization of digital well-being with intelligent computing systems.

Data Collection

This study employs a systematic literature review to gain a structured understanding of diverse perspectives on digital well-being within intelligent computing systems. A systematic literature review is recognized as a valid and reliable methodological approach to address emerging issues and integrate divergent viewpoints [41]. To bridge various perspectives and establish new theoretical foundations, this study follows the principles of systematic literature review proposed by Tranfield et al. (2003) [42]. The process is organized into four broad phases: (1) searching existing research, (2) screening relevant studies and approaches, (3) reviewing and evaluating focal studies on digital well-being with intelligent computing systems, and (4) conducting supplementary backward and forward searching. Figure 2 illustrates the data collection process.

Figure 2. Overview of Data Collection Process.



Databases = Web of Science, EBSCO, PubMed, and ACM Digital Library

In the initial phase, four primary databases—Web of Science, EBSCO, PubMed, and the Association for Computing Machinery (ACM) Digital Library—were utilized to identify relevant studies. The first publication search was conducted on August 15, 2022, with the final literature list updated on October 20, 2024, to ensure the inclusion of up-to-date studies.

The search strategy was designed by analyzing prior research and examining terminology used in the relevant scientific papers which were critically reviewed in this paper's initial scoping review phase. For the searching process, the initial keyword string was designed to focus on the intersection of technology and well-being across multidisciplinary fields by constructing a query that combined multiple thematic dimensions:

- ***Core Concepts:*** *The query incorporated terms related to wellbeing, such as "wellbeing" and "well-being," to capture diverse terminology used across disciplines.*
- ***Technological Scope:*** *Keywords like "system," "interface," "computer," and "technology" were included to ensure relevance to studies that involve digital and computational systems.*
- ***Intelligence and Interactivity:*** *To refine the focus on intelligent and adaptive technologies, terms such as "artificial intelligence," "AI," "intelligent," "interactive," "smart," "autonomous," and "digital" were included.*

Data Collection from the Web of Science

The Web of Science was chosen as the primary database for conducting a systematic literature search due to its comprehensive coverage of high-impact journals, conference proceedings, and other scholarly publications. The final query was adapted as follows:

TS=("wellbeing" OR "well-being") AND TS=("system" OR "interface" OR "computer" OR *"technology") AND TS=("artificial intelligence" OR "AI" OR "intelligent" OR "interactive" OR "smart" OR "autonomous" OR "digital")*

Boolean operators and wildcards were applied to broaden the search and accommodate variations in terminology. Advanced search filters also were employed to focus on peer-reviewed publications, including journal articles, conference proceedings, and review papers. The systematic search yielded an initial pool of 5,424 articles.

Data Collection from the EBSCO

The EBSCO database was utilized to conduct a comprehensive literature search, leveraging its extensive collection of resources spanning a wide array of academic disciplines. EBSCO was chosen for its strong interdisciplinary coverage, particularly in areas related to social sciences, computer science, and human-computer interaction, making it well-suited for exploring the digital aspects of well-being. The search string mirrored that of other databases:

("wellbeing" OR "well-being") AND ("system" OR "interface" OR "computer" OR "technology") AND ("artificial intelligence" OR "AI" OR "intelligent" OR "interactive" OR "smart" OR "autonomous" OR "digital")

The search was limited to peer-reviewed publications to ensure that only high-quality scholarly work was included. Also, in the EBSCO, the search was restricted to the abstracts of articles to focus on studies that explicitly address the targeted themes. The initial query yielded a total of 6,433 articles, encompassing a wide range of studies related to the human-computer interaction and digital well-being domains.

Data Collection from the PubMed

The PubMed database was chosen as a key resource for exploring studies at the intersection of digital well-being and intelligent systems due to its focus on health, biomedical research, and related fields. To align with the overarching research goals, the following search query was constructed to capture a wide range of relevant studies:

(("wellbeing" OR "well-being") AND ("system" OR "interface" OR "computer" OR "technology") AND (“artificial intelligence" OR "AI" OR "intelligent" OR "interactive" OR "smart" OR "autonomous" OR "digital"))

The initial query yielded 4,073 articles. This output reflects the strength of PubMed in identifying multidisciplinary research that links intelligent systems with digital wellbeing, particularly within the contexts of healthcare and user interaction.

Data Collection from the ACM Digital Library

The ACM Digital Library was selected for its specialized focus on computing and information technology research, encompassing both theoretical advancements and practical insights from academia and industry. Given its prominence in the field of computing, the ACM Digital Library was anticipated to offer unique and highly relevant contributions to understanding the intersection of digital well-being and intelligent systems. The search was designed to explore themes of digital well-being, particularly in the context of HCI. To capture a broad range of studies, the following search query was used:

AllField:(“wellbeing” OR “well-being” OR “digital wellbeing” OR “digital well-being”)

To ensure high relevance and quality, one advanced filter was applied to limit the results to research articles published under the ACM Special Interest Group on Computer-Human Interaction (SIGCHI). SIGCHI represents a core community in HCI research, making it a critical source for studies at the nexus of well-being and intelligent systems. The initial search yielded a total of 5,669 articles. This comprehensive set of results highlights the breadth of research contributions in the ACM Digital Library, particularly within the SIGCHI community, which has long been at the forefront of exploring the relationship between human-centered design, interaction, and user well-being.

Final Literature Sample

From the initial search, in total, 21,599 articles were identified. After that, the articles were reviewed based on their titles, abstracts, and index keywords, resulting in the remaining 218 articles. During this initial review process, five criteria were employed to further refine the data pool (Table 1).

Next, the remaining articles were reviewed and assessed in terms of their entire content. In this phase, a backward and forward search via cross-references was also conducted and twelve articles were included in the set of the review articles. Furthermore, 22 additional articles were included from other relevant sources based on the consultation with external researchers and practitioners who have expertise in related human-computer interaction fields. At the end of this entire review process, 240 articles were selected for the final literature sample.

Table 1. The Eligibility Criteria to Select the Articles for the Final Review Process.

Criteria	Guideline Descriptions
1	The article should be related to the targeted research areas and topics of this study.
2	The article should be peer-reviewed and categorized as an original research article.
3	The article should have well-defined research purposes to tackle the issue on design for digital well-being with intelligent computing systems in everyday contexts.
4	The article should point out the importance of investigating interactions between users and intelligent computing systems in their everyday behavioral decision-making contexts.
5	The article should contain practical aspects to create or evaluate the designed interactions for supporting users' digital well-being.

Sample Data Description

The chronological distribution of selected articles on digital well-being and intelligent computing systems (Figure 3) reveals an evolving landscape shaped by technological advancements and societal concerns. The earliest article in the reviewed literature dates back to 2008, marking the inception of academic discussions on this topic.

Between 2008 and 2016, research predominantly focused on user interactions with intelligent computing systems and interface features such as the internet, social media, and smartphones. These studies explored the impact of these technologies on subjective and emotional well-being, leveraging broad psychological theories and empirical findings on overall well-being. During this period, the discourse primarily reflected a reactive stance, emphasizing the potential of these technologies to enhance or impair users' emotional states.

A notable shift occurred in 2017, catalyzed by growing ethical concerns about the adverse effects of digital technologies on everyday life. This shift coincided with intensified debates in academia and industry about the ethical responsibilities of technology designers. Consequently, interest in digital well-being surged, with a significant peak in 2019. This period marked a paradigm shift, as global technology companies, influenced by user demand and public scrutiny, began prioritizing digital well-being as a cornerstone of their design ethics and business strategies. Research during this time focused on developing tools like Personal Informatics Tools (PITs) and Digital Self-Control Tools (DSCTs), aiming to empower users to manage their technology use proactively.

From 2022 onward, discussions of digital well-being have expanded beyond the development of user tools. Scholars have started addressing challenges related to emerging technologies such as AI and their implications for well-being. This phase of research is characterized by interdisciplinary approaches, integrating insights from HCI, ethics, and data science to identify new opportunities and limitations in fostering digital well-being. These discussions reflect the growing recognition of the complex interplay between intelligent systems, societal values, and the evolving expectations of digital users globally.

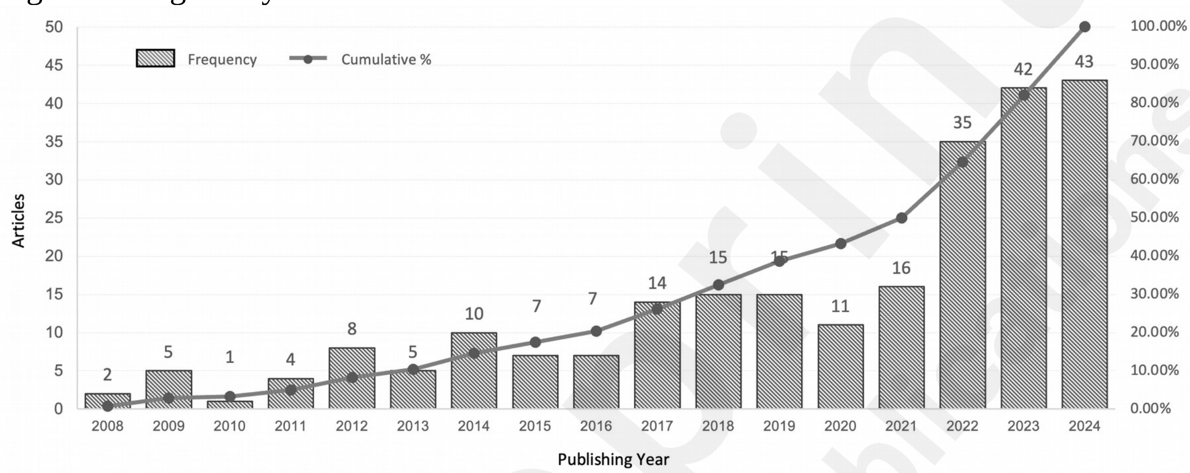


Figure 3. Publication Years of the Selected Articles on Digital Well-being and Intelligent Computing Systems.

Data Exploration: Emerging Perspectives on Digital Well-being and Intelligent Systems

After the data collection and screening process, an inductive data coding process was conducted for a systematic analysis of existing perspectives on digital well-being and intelligent computing systems. In this process, based on the SOR model and its three key components (i.e., stimulus, organism, and response), this paper utilized a coding scheme which was developed for each publication to carry out an affinity diagramming process with a purpose of standardizing various perspectives [43]. From this in-depth analysis on previous studies and approaches, three emerging perspectives were also clustered which can be incorporated to the development of a model of human-centered AI computing systems for digital well-being.

Finding 1. Three Implementation Areas of Intelligent Computing Systems for Digital Well-being

The previous studies and approaches were clustered with a focus on three emerging perspectives in terms of implementation areas and consequential benefits of intelligent computing systems for digital well-being: (1) users' overall well-being in daily HCIs; (2) design for behavioral changes; and (3) behavioral intervention technology.

First, well-being in daily interactions with computing systems has been studied through a variety of lenses (i.e., digital health, digital health technology, technology for mental health, or digital medicine) and under diverse human behavioral contexts over the past two decades. Among these various perspectives, “well-being in HCIs” is the broadest for considering technology as a tool for human flourishing and well-being [3]. Most related works aim to improve a user’s psychological and subjective well-being by developing interactive design/technology interventions along two pathways. The first pathway is formulating system design principles by employing relevant theories from positive psychology such as hedonic experience and self-determination theory [3, 44, 45]. The second pathway involves investigating certain well-being determinants from the theories in the first pathway such as autonomy, competence, and relatedness [3]. These well-being determinants typically serve as intentions for computing system design and criteria for evaluations in technology development processes.

However, the concept of well-being has been considered too broad to be scientifically defined because it reflects the various subjective statuses of individuals. Although previous studies have attempted to suggest tools for system design and development practices by grounding them in rigorous evidence-based empirical research, the major criticism of the perspective of well-being in HCIs is that implementation of relevant approaches is fragmented and unstructured [3, 46]. Furthermore, the notion of well-being has mainly been applied as a descriptive term for depicting current lifestyle trends. It has also been utilized as a conceptual keyword for implementing the human-centric approach with a focus on the consequential outcomes of system design practices [32]. Understandably, there have not been many academic attempts to integrate various perspectives from relevant fields into an overarching viewpoint of well-being as well as digital well-being and intelligent computing systems.

Second, the topic of design for behavioral changes has been researched from a more defined angle through focusing on explicit users’ short-term and long-term behavior changes [48]. For researchers and practitioners, designing for digital health means addressing various subjective aspects of human experiences that are hard to operationalize and measure [49]. In this regard, they have employed ample evidence and solid theories from the field of psychology that explain how to forge human attitudes and behaviors for specific system design aims [28]. These researchers and practitioners have understood the mechanism of human behavior and leveraged it as a solid foundation to create behavioral interventions that focus on human health and well-being. More recently, the focus on research and practice has begun to address the long-term consequences of each user’s behavior and their impact on well-being rather than just optimizing the moment of interaction with computing systems and technologies (e.g., delivery of interventions and usability of interfaces). For this reason, researchers have attempted to expand the perspective of design for behavioral change to design for habit change as well.

Niedderer et al. outlined the overview of design for behavioral change and expected challenges in understanding, evaluating, and implementing this theme by surveying private and public sector stakeholders [50]. They identified a significant disconnection between theoretical approaches and practical implementations caused by a lack of shared terminologies about individuals’ health and well-being. Regarding the perspective of design for habit change, Pinder et al. also pointed out the issue of heterogeneous perspectives and approaches on the concept of design for habit change in the field of HCI [51]. In response to the need for overarching perspectives, the authors integrated the three main theories of habit change (dual process theory, modern habit theory, and goal setting theory) into an explanatory framework by suggesting the “habit alternation model.” In addition, behavioral scientists have reported increased needs for novel approaches emphasizing the value of human-centered design to improve the effectiveness of behavior and habit change interventions via technology [52]. They have attempted to design and evaluate their behavioral intervention techniques within a real-world context, but they have faced a similar issue of lack of coherent understanding of the dynamics between human behavior and design/technology interventions [43, 54].

Last, the recent perspective of Behavioral Intervention Technology (BIT) is an actively studied and implemented subarea of design for behavior/habit change from the perspective of healthcare and medical areas. According to a study by Mohr et al. (2014) [55], the concept of BIT is defined as “the application of behavioral and psychological intervention strategies by using technological features to target behavioral, cognitive, and affective context and environment that support physical, behavioral, and mental health.” The development of various interactive systems has allowed behavioral scientists to actively conduct research about BITs. This research has generated several empirical findings that have revealed new methods to induce behavioral changes and further support individuals’ physical, behavioral, and mental health [36, 55, 56]. Researchers and practitioners have improved this macro perspective based on a systematic understanding of (1) how to utilize various state-of-the-art intelligent computing technologies, (2) who will use these technologies, and (3) whether the technology is actually useful for users. Most recently, under the keyword of personal informatics tools and digital medicine, various initiatives from related disciplines, including decision science and data science, have been developed to find new ways to forge behavioral changes and support well-being based on a set of individual behavior and preference data [24, 57, 58].

Previous BIT approaches have been mainly developed in the specific contexts of the healthcare setting and evaluated from the perspective of clinical aims [59]. However, a number of researchers and practitioners have commented on the limitations of BITs in terms of (1) the lack of theories informing their development of behavioral intervention technologies; (2) the lack of evaluation models for understanding how users interact with BITs; (3) the issue of users’ access to BITs and the costs they incur; (4) the negative aspects of users’ adherence to and engagement with BITs; and (5) the drawbacks of the integration of BITs into existing health delivery systems [48]. Because of these limitations, behavioral scientists have given increased attention to integrating fragmented perspectives on human-centric design into a solid overarching theory as well as to suggesting new principles for effective behavior intervention in the recent context of human-computer interactions [47].

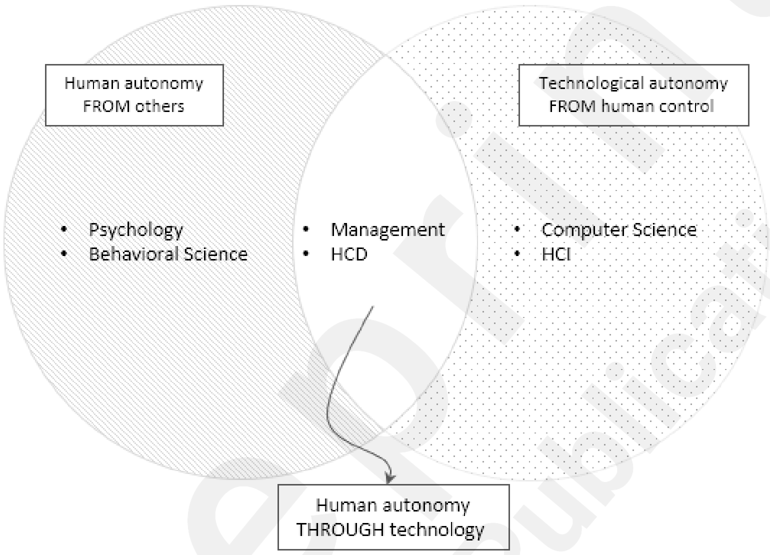
Based on the previous perspectives and approaches on digital well-being with intelligent computing systems, the three main observations emerged for a further consolidation. First, most previous perspectives about digital well-being with intelligent computing systems have paid more attention to the consequences of people’s behavioral decision-making. However, they recently emphasize the importance of considering diverse individual differences to improve the effectiveness of their interactions with the systems [50, 60]. Second, most existing works have underlined the importance of creating well-systemized and personalized interactions and interventions for users’ behaviors and their digital well-being. Recently, several approaches have concentrated on the importance of real-time monitoring and quantifying contextual differences around users to support their digital well-being [36, 56, 58, 61]. Third, according to the ongoing advancement of AI-powered systems, researchers and practitioners have struggled with making a bridge between research on human autonomy in HAIIs and the topics of digital well-being focusing on personalized user experience and human-centered AI technologies [3, 47, 59].

Finding 2. Conceptual Diversity on Human Autonomy with AI-powered Intelligent Systems

The review results also identified that the technological and societal shifts toward the active implementation of AI-powered computing systems led to increased recognition of the concept of “autonomy” between human and AI-powered intelligent systems in various disciplines [19, 27, 62].

As illustrated in Figure 4, in psychology, the concept of human autonomy is considered one of the basic psychological needs from the perspective of "human autonomy from others, including people as well as environmental factors [63]." From this perspective, psychologists and behavioral scientists have focused on behavioral interventions to change people's attitudes and behaviors in positive ways by investigating the relationship between human autonomy and the behavioral decision-making process [46]. Researchers in computer science and engineering have attempted to address how to design autonomous technologies and products to support human autonomy and well-being [27]. Specifically, the field of HCI has shown a keen interest in the design of autonomous systems and personalized AI interfaces within the perspective of "technological autonomy from active human input and control [64]." In the management science and design fields, several recent papers have also emphasized the significant role of "human autonomy through technology" in the new era of AI and smart products [57, 65].

Figure 4. Various Interpretations of the Concept of Autonomy in Related Disciplines.



Despite practitioners and researchers' efforts to ensure users' increased autonomy in AI interactions, it appears that design for human-centered AI systems has been hindered by the lack of conceptual precision. The varying approaches developed in the aforementioned disciplines tend to focus on different aspects of autonomy that can be limiting for researchers and practitioners to have a holistic understanding of autonomy regarding its meaning, causes and manifestations in HAIIs. In particular, User Experience (UX) designers and system developers continue to struggle with creating human-centered AI systems [17, 62]. The challenge entails the fulfilment of two conflicting user needs: users expect their AI systems to take over their tiresome or time-consuming work, but at the same time, they resist being managed by highly AI systems. Several cases have recently been reported in which autonomous and AI systems unwittingly overstep and hinder users' autonomy (e.g., a coercive health monitoring system that forces a patient to be physically active when inappropriate [66] and Uber drivers resisting to be managed by the company's algorithmic app [41]).

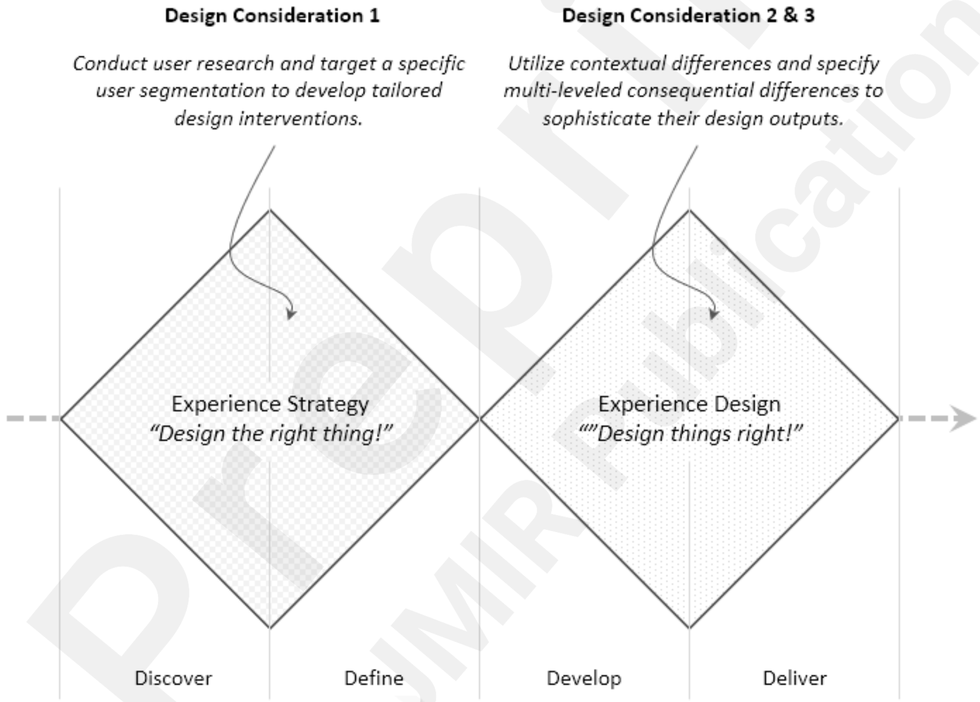
Finding 3. Developing and Evaluating Process for Digital Well-being with AI Systems

Existing initiatives have pointed out that the current gap between abstract theoretical perspectives and actionable methodologies should be bridged in order to help with the development and evaluation of daily AI systems for digital well-being. Based on discussions on digital well-being and AI computing systems, two practical questions emerged from the relevant initiatives which researchers and practitioners have struggled with: *(1) how can researchers and practitioners identify* *applicable strategies for developing AI systems for digital well-being?* and *(2) how can they evaluate results to establish which AI systems are more effective for improving users' digital well-being?* Further, to tackle these questions, researchers and practitioners also have a consensus that it would be beneficial to have an overarching viewpoint in order to design more "human-centered" AI computing systems for digital well-being.

In this regard, this paper identified that these researchers' and practitioners' pain points can be reframed within the initial framework of this study derived from the SOR Model. Specifically, this paper clarified core contribution aspects of synthesizing various perspectives from diverse fields into the research and design process toward human-centered AI systems for digital well-being as follows:

- ***Consideration 1.*** *Considering individual differences for the organism component.*
- ***Consideration 2.*** *Utilizing contextual differences for the stimulus component.*
- ***Consideration 3.*** *Specifying consequential differences for the response and outcome components.*

Figure 5. The Developing Process for Digital Well-being with AI Systems.



For example, within the general perspective, developing process for digital well-being with AI systems can contain two main parts (Figure 5), experience strategy (designing the right thing) and experience design (designing things right) based on the revamped double diamond design process [67]. According to the reflection on previous literature, in the first part, researchers and practitioners tend to figure out the pain and gain points of targeted users and customers by implementing various user research methods to identify their core challenges. At this point, within the perspective of the initial framework on digital well-being with AI systems, they conduct user research to profile their users in terms of identifying individual differences (Consideration 1). Based on outcomes of the user research, researchers and practitioners attempt to target a specific user segmentation and develop tailored design solutions and behavior interventions for this segmentation. To achieve this goal, they also utilize various contextual differences as resources and specify multi-leveled consequential differences as evidence to evaluate and improve the sophistication of their design outputs (Consideration 2 & 3). In the second part, researchers and practitioners aim to design human-centered computing systems or technology features to provide targeted UX contexts as well as nudge users to perform specific activities or behaviors.

Data Synthesis: The Development of Human-centered AI for Digital Well-being Model

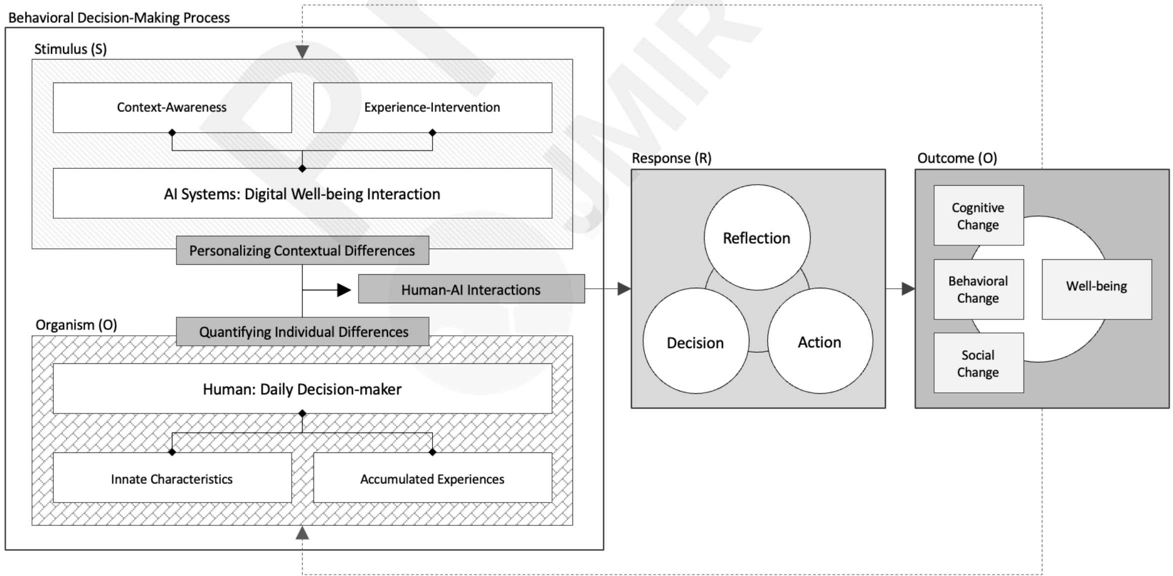
Based on the data exploration process described above, this paper synthesized the findings by suggesting an overarching perspective, namely the Human-centered AI for Digital Well-being (HCAI-DW) model. To develop the more applicable and structured model, a further round of in-depth review was organized wherein the outlined understanding of digital well-being and AI systems was intensively discussed. Further, five professors and 17 graduate students who study in the fields of HCI and human-centered design were invited in the initial and final review sessions to share their opinions and feedback for the improvement of the HCAI-DW model. The primary goal of the review sessions was to model this literature review study and to evaluate the proposed model from external researchers' and practitioners' perspectives. In this section, the paper introduces an overview of the HCAI-DW model and its subcomponents by synthesizing the literature review findings.

Overview

The HCAI-DW model was revamped based on the SOR model to provide a descriptive simplification of how AI systems can support everyday experiences in a digital well-being-improving way.

Figure 6 frames the whole mechanism of digital well-being-improving approaches with AI systems. This diagram of the HCAI-DW model illustrates each aspect of the four components for creating human-centered AI systems for digital well-being: (1) the part of the organism for describing individuals as daily behavioral decision-makers; (2) the part of the stimulus representing system intervention; (3) the part of the response that displays the decision-action-reflection loop; and (4) the part of the outcome covering consequent changes after responding within the perspective of digital well-being. The following sections provide explanations of these components of the model.

Figure 6. Human-centered AI for Digital Well-being Model (HCAI-DW Model).



Organism: Daily Decision Makers

In the HCAI-DW model, the component of the organism can be determined by users' various individual differences in their behavioral decision-making situations with AI systems. The HCAI-DW model seeks individual differences to provide optimized and personalized interactions [47].

Individuals tend to make behavioral decisions based on their innate characteristics or accumulated experiences. Profiling the preference or behavioral data of these individuals as well as designing tailored interactions would allow a high level of efficiency and effectiveness of digital well-being interventions [36, 56]. Moreover, the core notion of this model is that AI-powered systems and technologies could be understood as a system platform with the aggregation of huge amounts of data across many users. Based on this abundance of data, it becomes possible to develop and apply a machine learning or deep learning algorithm for each individual to enable a more sophisticated experience-behavior induction [56, 68, 69]. As a result, the data can be utilized as an insightful resource to improve the quality of optimal support and to develop more deeply tailored and personalized interactions by covering various differences in individuals' subjective aspects of decision-making. For this reason, the model suggests that the perspective with a consideration of individuals as "daily decision-makers" can be a key notion for answering important academic and practical questions on design for digital well-being with human-centered AI computing systems.

Stimulus: Digital Well-being Interactions

The stimulus component reflects the notion that researchers and practitioners have considered their AI system features as a behavioral intervention for their users. As we identified from the systematic literature review process, several previous initiatives have addressed design issues and activities by mainly focusing on users' interactions with intelligent systems as just a design theme or as one of the evaluation aspects for testing the interface and interaction design [3, 70]. In the HCAI-DW model, however, this stimulus part is separated into two different phases: a context-awareness phase and an experience-intervention phase. First, the concept of the context-awareness phase comes from the theme of quantified-self and personal informatics [56]. In the context-awareness phase, AI systems need to monitor, quantify, and digitize significant aspects of UX using the contextual differences around a targeted individual in the design to produce effective digital well-being interactions. Second, the concept of the experience-intervention phase is based on the concept of BIT from the area of behavioral science [61, 71]. In the experience-intervention phase, well-systemized and personalized interventions are provided for individuals to optimize their autonomy status as well as encourage changes of their responses and experiences. Thus, the HCAI-DW model considers AI systems as digital well-being-supporting interactions for each user.

Response: Decision-action-reflection Loop

The response component in the HCAI-DW model covers not only outcomes of the behavioral decision-making interactions with AI systems but also the on-going process of experiencing and reflecting on an individual's decision-making interactions with AI systems. To gain a better understanding of digital well-being in these interactions, it is necessary to distinguish between two perspectives: (1) one that considers the response as users' terminating behavior after processing the behavioral decision-making and (2) another that considers the response as users' experiencing a consecutive phase of decision-making interactions. In most previous studies and practices, researchers and practitioners have focused on people's decisions and behaviors as outcomes of their context-specific interactions with designed intelligent systems. They have also measured these outcomes to evaluate the effectiveness of the interactions. However, this fragmented perspective has led previous researchers to miss the core component of the behavioral decision-making process: reflection. In contrast, the HCAI-DW model emphasizes the value of figuring out the cognitive and behavioral mechanism before (decision), during (action), and after (reflection) conducting specific actions within a cyclical long-term viewpoint.

Outcome: From Cognitive Change to Social Change

In terms of outcomes, it is possible to draw a connection between previous implementation domains and the notion of specifying consequential differences. There are a variety of levels of outcomes that are affected by a user's behavioral decision-making experience with AI systems. Based on existing literature, the HCAI-DW model categorizes these outcomes in three levels of individuals' experiential results: cognitive change, behavioral change, and social change. The impact of behavioral decision-making interactions with AI systems in daily contexts has been understood from the perspective of the point at which the users believe that satisfaction of needs has occurred. Most previous perspectives recommend providing "autonomy-optimize" interactions to improve people's daily lives [4, 62] . For example, the model for Motivation, Engagement, and Thriving in User eXperience (METUX) can be the typical example of a proposed model to bridge self-determination theory and design practices. The METUX model represents psychological needs that can be fulfilled within different levels of technology-mediated experience (e.g., adoption, interface, task, behavior, life, and society). The model does not develop technology interventions that are "need-satisfying" at one level but "need-frustrating" at another by considering the hierarchical structure of UX. However, it has a limitation as to how researchers and practitioners differentiate the spheres of experience in their developmental practices and what their theoretical backgrounds are.

This limitation reveals the need for more systematic perspectives for differentiating consequent aspects of design and technology interventions on experiences. Most of the previous approaches target the single optimal balancing point. This reflects the ideal consequence of their design interventions and strategies. However, there are multi-layered aspects of experiential outcomes that occur with different individuals. The diversity of these aspects indicates that these approaches have not only failed to focus on the behavioral decision-making mechanism but have also failed to specify various consequential differences between people. As a result, researchers and practitioners have attempted to ask individuals to make every effort to change their own decision-making mechanisms through teaching and training [4, 35]. Despite these initiatives, it is hard to argue that these approaches are fundamentally based on well-reflected "human-centered" perspectives. For this reason, the suggested approach of the HCAI-DW model for the outcome component is helpful for developing effective digital well-being interactions that can assess both the short-term and long-lasting aspects of UX. The model can also be useful to systematically synthesize aspects of the wider focus of research in diverse fields of study by differentiating between the fundamental mechanism of the behavioral decision-making process and the consequential changes as an expected and targeted outcome.

Discussion and Future Directions

In this paper, the HCAI-DW model was developed to frame how AI systems can support an individual's behavioral decision-making experiences and behavioral changes in ways that optimize their daily digital well-being. This paper grounded the overarching perspective of human-centered AI systems for users' digital well-being in evidence-based academic research and well-established perspectives from relevant practical fields. Thus, it is expected that the HCAI-DW model could improve existing technology development approaches by providing a systematic way to encode and utilize the core factors that drive digital well-being with AI computing systems. Moreover, based on its purpose for intuitive and practical use, the model was developed and visualized to address the emerging needs of researchers and practitioners who are trying to apply insightful theories and approaches to design various aspects of human experience in their development processes. For this reason, researchers and practitioners can expect the model to create effective interactions of AI systems by tailoring individual and contextual differences reflective of people's decision-making mechanisms.

Limitations

This paper provides insights into human-centered AI systems for users' daily digital well-being by incorporating a systematic literature review method. To provide the comprehensive and multidisciplinary overview of the most relevant literature, the four data sources were also used as the primary data source. However, as aforementioned, existing initiatives on the concept of digital well-being with intelligent computing systems have been shared through varied terms and keywords. That is the reason why this paper employed the overall level of search terms in the first phase of the data collection to address this fragmented circumstance. Despite this initiative, there might be other relevant perspectives and approaches on designing intelligent systems for digital well-being from different angles or disciplinaries which are not fully covered in this paper. Further, a limited number of relevant studies which are explicitly use the term of digital well-being and AI systems are available in spite of the circumstance that the topic has attracted considerable interest from many different fields in academia and industry. Thus, it is invited to conduct additional review studies from relevant disciplinaries within a consideration of the heterogeneity of existing studies in terms of their ways of describing the concept of designing for digital well-being, usage contexts of AI systems, research methods, perspectives, and outcomes.

In addition, the development of the HCAI-DW model should be considered a steppingstone toward providing a structured and applicable understanding of design for well-being with AI systems instead of a completed and solid framework. The model focused on synthesizing existing discussions on the topic within the overarching perspective for further initiatives on creating more human-centered AI systems to support users' daily digital well-being. It means that this initial model may not be applicable or generalizable to all usage contexts of digital well-being and AI systems. For this reason, in future studies, testing and validating through empirical research in actual design scenes could help refine the HCAI-DW model as well as the findings of this paper.

Future Directions

This study can also facilitate future research and practical system development activities in terms of the advancement of novel principles for digital well-being with AI systems in various daily HCIs. There are three challenges for future research and practice based on findings from the systematic literature review: (1) developing new measurements for digital well-being with AI systems; (2) considering ethical issues in AI-powered technology intervention; and (3) considering individual decision-making contexts for hyper-personalization. In the following sections, these challenges will be discussed in terms of exploring research opportunities to enhance the body of knowledge on design for digital well-being with AI systems.

New Evaluation Measurements for Digital Well-being with AI Systems

Several previous studies pointed out that HCI professionals have addressed the issues of reliability and validity of existing measures to evaluate the subjective aspects of well-being in technology use [35, 71]. Within the perspective of the HCAI-DW model, this paper emphasizes that there could be various levels of outcomes that are affected by individuals' behavioral decisions in daily life. However, the lack of well-systemized and validated measurement tools that can be easily used or universally employed to evaluate the short-term or long-term impacts of designed technology interventions is an issue. The effectiveness of technology intervention is difficult to measure and evaluate [72]. Therefore, new methods to measure the impact of behavioral intervention need to be developed rather than just adapted from adjacent domains.

Ethical Issues in AI-powered Technology and System Interventions

According to extant literature, the concept of digital well-being in HCIs focuses on making a positive change in people's lives through technology intervention. However, technology intervention needs to be considered within the perspective of users who are affected by it. Intervention is value-neutral, but there is always a risk that it could be used in a negative and unethical way for people because an intervention is based on the manipulation of human behavior [73]. For example, by utilizing this decision-making mechanism, governments or corporations might be able to impose intended agendas on individuals [51]. Since they could easily take control of individuals' lives by implementing designed technology interventions, there has been increased concern about risks for problematic and unethical interventions [74]. Therefore, researchers and practitioners must pay attention to the possibility of misuse as well as the negative impacts of an intervention. Furthermore, digital privacy can be another issue with technology intervention. Within the perspective of the HCAI-DW model, it is necessary to figure out individuals, their contexts, and the impacts of behavioral decision-making to provide tailored and personalized interventions. In a real-world context, there is always an issue with information privacy for data collection, and it is necessary to consider the rights of individuals within the perspective of privacy protection.

Individual Decision-making Contexts for Hyper-personalization

In today's era of AI, researchers and practitioners have attempted to personalize UX based on individuals' previous histories of interaction in order to improve their daily lives [17, 18, 58]. This trend, which has been called "hyper-personalization," aims to leverage AI and real-time data and to deliver more relevant content, products, service information, and UX to each individual. Despite the advent of AI technology, few studies have empirically and explicitly investigated how to, within the viewpoint of design for digital well-being with AI systems, utilize this technological concept—one that fosters active engagement, sustained behavioral change, or well-being [17, 50, 65]. However, the concept of hyper-personalization can be understood as considering individual, contextual, and consequent differences based on the HCAI-DW model. Since the model has covered the contemporary issue of human-technology interaction in fields relevant to AI, the model can cover the general level of hyper-personalization in design for digital well-being. Therefore, it is necessary to find more actionable principles regarding how to design AI systems for hyper-personalization based on considerations of individual differences in daily decision-making contexts, thereby increasing the impact of AI technologies on sustained behavior change and ultimately enhancing the various aspects of individuals' digital well-being.

Conclusion

In this paper, the everyday behavioral decision-making interaction is regarded as a core concept for synthesizing existing approaches to design for digital well-being with AI systems. This paper reviewed the fragmented and inconsistent perspectives and bridged these macro perspectives by developing the HCAI-DW model. Furthermore, this paper addressed how AI computing systems can support users' behavioral decision-making experiences and related behaviors in a way that optimizes their digital well-being. Therefore, it is expected that new perspectives based on this paper could expand to new boundaries where researchers and practitioners could discuss a "new type of human" who always interacts with everyday AI systems for their digital well-being.

Conflicts of Interest

None declared.

Appendix

The list of the reviewed 240 articles is available at the following link:
https://docs.google.com/spreadsheets/d/10vlj5vBF8FFY4rIkoaeTuBpD1jxvBAxu-4idHo_ug28/edit?gid=0#gid=0

Abbreviations

ACM: Association for Computing Machinery

AI: Artificial Intelligence
BIT: Behavioral Intervention Technology
DSCTs: Digital Self-control Tools
HAII: Human-AI Interaction
HCAI: Human-centered AI
HCAI-DW: Human-centered AI for Digital Well-being
HCI: Human-computer Interaction
ICT: Information and Communication Technology
METUX: Motivation, Engagement, and Thriving in User eXperience
PITs: Personal Informatics Tools
SOR: Stimulus-Organism-Response
UX: User Experience

References

1. Burr C, Taddeo M, Floridi L. The ethics of digital well-being: a thematic review. Science and Engineering Ethics. 2020;26(4):2313–2343. [doi:10.1007/s11948-020-00175-8]
2. Cecchinato ME, Rooksby J, Hiniker A, Munson S, Lukoff K, Ciolfi L, Thieme A, Harrison D. Designing for digital wellbeing: a research and practice agenda. In Extended Abstracts of the SIGCHI Conference on Human Factors in Computing Systems. 2019:1–8. [doi:10.1145/3290607.3298998]
3. Peters D, Ahmadpour N, Calvo RA. Tools for wellbeing-supportive design: features, characteristics, and prototypes. Multimodal Technologies and Interaction. 2020;4(3):40. [doi: 10.3390/mti4030040]
4. Calvo RA, Peters D. Positive computing: technology for wellbeing and human potential. MIT Press; 2014. ISBN:9780262028158.
5. Desmet PM, Pohlmeyer AE. Positive design: an introduction to design for subjective well-being. International Journal of Design. 2013;7(3):21–33.
6. Gaggioli A, Villani D, Serino S, Banos R, Botella C. Positive technology: designing e-experiences for positive change. Frontiers in Psychology. 2019;10:1571. [doi:10.3389/fpsyg.2019]
7. Hassenzahl M, Eckoldt K, Diefenbach S, Laschke M, Lenz E, Kim J. Designing moments of meaning and pleasure: experience design and happiness. Int J Design. 2013;7(3):21–31.
8. Kim YH, Jeon JH, Choe EK, Lee B, Kim K, Seo J. TimeAware: leveraging framing effects to enhance personal productivity. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. 2016:272–283. [doi:10.1145/2858036.2858428]
9. Klapperich H, Laschke M, Hassenzahl M, Becker M, Cürlis D, Frackenpohl T, Köhler H, Ludwigs K, Tippkämper M. Mind the gap: a social practice approach to wellbeing-driven design. In: Design for Wellbeing. Routledge. 2019:154–169.
10. Ko M, Choi S, Yatani K, Lee U. Lock n' LoL: group-based limiting assistance app to mitigate smartphone distractions in group activities. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. 2016:998–1010. [doi:10.1145/2858036.2858568]
11. Li AY, Chau CL, Cheng C. Family and work-related consequences of addiction to organizational pervasive technologies. Information & Management. 2019;48(2-3):88–95. [doi: 10.1016/j.im.2011.01.004]
12. Okeke F, Sobolev M, Dell N, Estrin D. Good vibrations: can a digital nudge reduce digital overload? Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '18). 2018:1–12. [doi: 10.1145/3229434.3229463]

13. Pohlmeyer AE. How design can (not) support human flourishing. In: Positive psychology interventions in practice. Springer, Cham. 2017:235–255.
14. Thomas V, Azmitia M, Whittaker S. Unplugged: exploring the costs and benefits of constant connection. Computers in Human Behavior. 2016;63:540–548. [doi:10.1016/j.chb.2016.05.078]
15. Monge Roffarello A, De Russis L. The race towards digital wellbeing: issues and opportunities. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '19);. 2019:1–14. [doi: 10.1145/3290605.3300616]
16. Shin Y, Yoon J. Towards designing human-centered time management interfaces: the development of 14 UX design guidelines for time-related experiences in mobile HCI. Adjunct Publication of the 23rd International Conference on Mobile Human-Computer Interaction (MobileHCI '21). 2021:1–7. [doi:10.1145/3447527.3474861]
17. Amershi S, Weld D, Vorvoreanu M, Fourney A, Nushi B, Collisson P, Suh J, Iqbal S, Bennett PN, Inkpen K, Teevan J. Guidelines for human-AI interaction. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. 2019:1–13. [doi:10.1145/3290605.3300233]
18. Howard J. Artificial intelligence: implications for the future of work. Am J Ind Med. 2019;62(11):917–926. [doi:10.1002/ajim.23037]
19. Shneiderman B. Human-centered artificial intelligence: reliable, safe & trustworthy. International Journal of Human–Computer Interaction. 2020;36(3):495–504. [doi:10.1080/10447318.2020.1741118]
20. Bonacini L, Gallo G, Scicchitano S. Working from home and income inequality: risks of a 'new normal' with COVID-19. Journal of Population Economics. 2021;34(1):303–360. [doi:10.1007/s00148-020-00800-7]
21. Baidu. How coronavirus is accelerating a future with autonomous vehicles. MIT Technology Review. 2020. Available at: https://www.technologyreview.com/2020/05/18/1001760/how-coronavirus-is-accelerating-autonomous-vehicles/. [Accessed October 20, 2024].
22. CB Insights. Reopening: the tech-enabled office in a post-COVID world. Available at: https://www.cbinsights.com/research/report/reopening-office-tech-work-post-covid/. [Accessed October 20, 2024].
23. Lanaj K, Johnson RE, Barnes CM. Beginning the workday yet already depleted? consequences of late-night smartphone use and sleep. Organ Behav Hum Decis Process. 2014;124(1):11–23. [doi:10.1016/j.obhdp.2014.01.001]
24. Lee YK, Chang CT, Lin Y, Cheng ZH. The dark side of smartphone usage: psychological traits, compulsive behavior and technostress. Computers in Human Behavior. 2014;31:373–383. [doi: 10.1016/j.chb.2013.10.047]
25. Monge Roffarello A, De Russis L. Designing technology that promotes users' digital wellbeing. XRDS: Crossroads, The ACM Magazine for Students. 2021;28(1):14–18. [doi: 10.1145/3481823]
26. Satchell C, Dourish P. Beyond the user: use and non-use in HCI. Proceedings of the 21st Annual Conference of the Australian Computer-Human Interaction Special Interest Group: Design: Open 24/7 (OZCHI '09). 2009:9–16. [doi:10.1145/1738826.1738829]
27. Peters D, Calvo RA, Ryan RM. Designing for motivation, engagement and wellbeing in digital experience. Frontiers in Psychology. 2018;9:797. [doi: 10.3389/fpsyg.2018.00797]
28. Smits M, Kim CM, van Goor H, Ludden GDS. From digital health to digital well-being: systematic scoping review. J Med Internet Res. 2022 Apr 4;24(4):e33787. [doi: 10.2196/33787]. [

29. Ames MG. Managing mobile multitasking: the culture of iPhones on Stanford campus. In Proceedings of the 2013 Conference on Computer Supported Cooperative Work. 2013:1487–1498. [doi:10.1145/2441776.2441945]
30. Chakraborty K, Basu D, Kumar KV. Internet addiction: consensus, controversies, and the way ahead. Indian Journal of Psychiatry. 2010:123–132. [doi:10.4103/0019-5545.64583]
31. Dabbish L, Mark G, González VM. Why do I keep interrupting myself? Environment, habit, and self-interruption. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. 2011:3127–3130. [doi:10.1145/1978942.1979405]
32. Douglas AC, Mills JE, Niang M, Stepchenkova S, Byun S, Ruffini C, Lee SK, Loutfi J, Lee JK, Atallah M, Blanton M. Internet addiction: meta-synthesis of qualitative research for the decade 1996–2006. Computers in Human Behavior. 2008;24(6):3027–3044. [doi:10.1016/j.chb.2008.05.009]
33. Oulasvirta A, Rattenbury T, Ma L, Raita E. Habits make smartphone use more pervasive. Personal and Ubiquitous Computing. 2012;16(1):105–114. [doi: 10.1007/s00779-011-0412-2]
34. Verduyn P, Lee DS, Park J, Shablack H, Orvell A, Bayer J, Ybarra O, Jonides J, Kross E. Passive Facebook usage undermines affective well-being: experimental and longitudinal evidence. Journal of Experimental Psychology: General. 2015;144(2):480–488.
35. Peters D, Ahmadpour N. Digital wellbeing through design: evaluation of a professional development workshop on wellbeing-supportive design. Proceedings of the 32nd Australian Conference on Human-Computer Interaction (OzCHI '20). 2021:148–157. [doi: 10.1145/3441000.3441008]
36. Shin Y, Kim C, Yoon J. Behavioural intervention technology in UX design: conceptual review, synthesis, and research direction. Congress of the International Association of Societies of Design Research. 2022:450–465.
37. Jacoby J. Stimulus-organism-response reconsidered: an evolutionary step in modeling (consumer) behavior. J Consum Psychol. 2002;12(1):51–57.
38. Mehrabian A, Russell JA. An approach to environmental psychology. Cambridge, MA: MIT Press. 1974. ISBN:9780262131079.
39. Jai TM, O'Boyle MW, Fang D. Neural correlates of sensory-enabling presentation: an fMRI study of image zooming and rotation video effects on online apparel shopping. J Consum Behav. 2014;13(5):342–350. [doi:10.1002/cb.1476]
40. Tai SH, Fung AM. Application of an environmental psychology model to in-store buying behaviour. The International Review of Retail, Distribution and Consumer Research. 1997;7(4):311–337. [doi:10.1080/095939697342914]
41. Lee JG, Kim KJ, Lee S, Shin DH. Can autonomous vehicles be safe and trustworthy? Effects of appearance and autonomy of unmanned driving systems. International Journal of Human-Computer Interaction. 2015;31(10):682–691. [doi:10.1080/10447318.2015.1070547]
42. Tranfield D, Denyer D, Smart P. Towards a methodology for developing evidence-informed management knowledge by means of systematic review. British Journal of Management. 2003;14(3):207–222. [doi:10.1111/1467-8551.00375]
43. Holtzblatt K, Wendell JB, Wood S. Rapid contextual design: a how-to guide to key techniques for user-centered design. Elsevier. 2004.
44. Fogg BJ. Persuasive technology: using computers to change what we think and do. Ubiquity. 2002(December):32. [doi:10.1145/764008.763957]
45. Keyes CL, Annas J. Feeling good and functioning well: distinctive concepts in ancient philosophy and contemporary science. J Posit Psychol. 2009;4(3):197-201.

doi:10.1080/17439760902844228.
46. Klapperich H, Laschke M, Hassenzahl M. The positive practice canvas: gathering inspiration for wellbeing-driven design. In: Proceedings of the 10th Nordic Conference on Human-Computer Interaction. 2018:74–81. [doi:10.1145/3240167.3240209]
47. Shin Y. Supporting users' decision-making experiences through hyper-personalized human-technology interactions. Proceedings of Designing Interactive Systems Conference (DIS '22 Companion). 2022:8–11. [doi:10.1145/3532107.3532873]
48. Consolvo S, McDonald DW, Landay JA. Theory-driven design strategies for technologies that support behavior change in everyday life. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. 2009:405–414. [doi:10.1145/1518701.1518766]
49. Dodge R, Daly A. The challenge of defining wellbeing. International Journal of Wellbeing. 2012;2(3):222–235. [doi:10.5502/ijw.v2i3.4]
50. Niedderer K, Ludden G, Clune S, Lockton D, Mackrill J, Morris A, Cain R, Gardiner E, Evans M, Gutteridge R, Hekkert P. Design for behaviour change as a driver for sustainable innovation: challenges and opportunities for implementation in the private and public sectors. International Journal of Design. 2016;10(2):67–85.
51. Pinder C, Vermeulen J, Cowan BR, Beale R. Digital behaviour change interventions to break and form habits. ACM Transactions on Computer-Human Interaction (TOCHI). 2018;25(3):15. [doi: 10.1145/3196830]
52. Stawarz KM, Cox AL. Designing for health behavior change: HCI research alone is not enough. CHI'15 workshop: Crossing HCI and Health: Advancing Health and Wellness Technology Research in Home and Community Settings. 2015.
53. Direito A, Walsh D, Hinbarji M, Albatal R, Tooley M, Whittaker R, Maddison R. Using the intervention mapping and behavioral intervention technology frameworks: development of an mHealth intervention for physical activity and sedentary behavior change. Health Education & Behavior. 2018;45(3):331–348. [doi:10.1177/1090198117752783]
54. Iosifidis G, Charette Y, Airoldi EM, Littera G, Tassiulas L, Christakis NA. Using rigorous methods to advance behaviour change science. Nat Hum Behav. 2018;2(11):797–799. [doi:10.1038/s41562-018-0471-8]
55. Mohr DC, Schueller SM, Montague E, Burns MN, Rashidi P. The behavioral intervention technology model: an integrated conceptual and technological framework for eHealth and mHealth interventions. Journal of Medical Internet Research. 2014;16(6):e3077. [doi: 10.2196/jmir.3077]
56. Kersten-van Dijk ET, Westerink JH, Beute F, IJsselsteijn WA. Personal informatics, self-insight, and behavior change: a critical review of current literature. Hum Comput Interact. 2017;32(5-6):268–296. doi:10.1080/07370024.2016.1276456.
57. Raff S, Wentzel D, Obwegeser N. Smart products: conceptual review, synthesis, and research directions. Journal of Product Innovation Management. 2020;37(5):379–404. [doi: 10.1111/jpim.12544]
58. Walch K. The seven patterns of AI. Forbes; 2019. Available at: https://www.forbes.com/sites/cognitiveworld/2019/09/17/the-seven-patterns-of-ai/#3c6fbc1012d0 [Accessed October 20, 2024].
59. Dobkin BH, Dorsch AK. The evolution of personalized behavioral intervention technology: will it change how we measure or deliver rehabilitation? Stroke. 2017;48(8):2329–2334. [doi:10.1161/STROKEAHA.117.016620]
60. Hermsen S, Renes RJ, Frost J. Persuasive by design: a model and toolkit for designing evidence-based interventions. Creating the Difference. 2014;74.

61. Russ TC, Woelbert E, Davis KA, Hafferty JD, Ibrahim Z, Inkster B, John A, Lee W, Maxwell M, McIntosh AM, Stewart R. How data science can advance mental health research. Nature Human Behaviour. 2019;3(1):24–32. [doi:10.1038/s41562-018-0470-9]
62. Calvo RA, Peters D, Johnson D, Rogers Y. Autonomy in technology design. In Extended Abstracts of the SIGCHI Conference on Human Factors in Computing Systems. 2014:37–40. [doi:10.1145/2559206.2560468]
63. Ryan RM, Deci EL. On happiness and human potentials: a review of research on hedonic and eudaimonic well-being. Annual Review of Psychology. 2001;52(1):141–166. [doi:10.1146/annurev.psych.52.1.141]
64. Zanker M, Rook L, Jannach D. Measuring the impact of online personalisation: past, present and future. International Journal of Human-Computer Studies. 2019;131:160–168. [doi:10.1016/j.ijhcs.2019.06.006]
65. Verganti R, Vendraminelli L, Iansiti M. Innovation and design in the age of artificial intelligence. Journal of Product Innovation Management. 2020(37):212–227. [doi:10.1111/jpim.12523]
66. García-Sáez G, Rigla M, Martínez-Sarriegui I, Shalom E, Peleg M, Broens T, Pons B, Caballero-Ruíz E, Gómez EJ, Hernando ME. Patient-oriented computerized clinical guidelines for mobile decision support in gestational diabetes. J Diabetes Sci Technol. 2014;8(2):238–246. [doi:10.1177/1932296814526492]
67. Nessler D. How to apply a design thinking, HCD, UX or any creative process from scratch. Available at: https://medium.com/digital-experience-design/how-to-apply-a-design-thinking-hcd-ux-or-any-creative-process-from-scratch-b8786efbf812. [Accessed October 20, 2024].
68. Hirsh JB, Kang SK, Bodenhausen GV. Personalized persuasion: tailoring persuasive appeals to recipients' personality traits. Psychol Sci. 2012;23(6):578–581. [doi:10.1177/0956797611436349]
69. Shin Y, Kim J. Data-centered persuasion: nudging user's prosocial behavior and designing social innovation. Computers in Human Behavior. 2018;80:168–178. [doi:10.1016/j.chb.2017.11.009]
70. Harlow LL, Oswald FL. Big data in psychology: introduction to the special issue. Psychol Methods. 2016;21(4):447–457.
71. Law EL, Van Schaik P, Roto V. Attitudes towards user experience (UX) measurement. International Journal of Human-Computer Studies. 2014;72(6):526–541. [doi:10.1016/j.ijhcs.2013.09.006]
72. Hermes ED, Lyon AR, Schueller SM, Glass JE. Measuring the implementation of behavioral intervention technologies: recharacterization of established outcomes. J Med Internet Res. 2014;21(1):e11752. [doi:10.2196/11752]
73. Page RE, Kray C. Ethics and persuasive technology: an exploratory study in the context of healthy living. Proceedings of the 12th International Conference on Human Computer Interaction with Mobile Devices and Service. 2010:527–530.
74. Jun GT, Carvalho F, Sinclair N. Ethical issues in designing interventions for behavioural change. In: Proceedings of Design Research Society 2018.