Tailoring Health: Contextual Variables In Health Recommender Systems*

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Abstract

hrs have emerged as a crucial tool in personalized healthcare, offering tailored recommendations to promote healthy behaviors and prevent diseases. The effectiveness of these systems hinges on their ability to accurately personalize recommendations based on contextual variables. This research investigates the contextual variables currently employed by Health Recommender Systems (HRSs), addressing two key research questions: (1) Which contextual variables are currently used in HRSs? and (2) How can these variables be categorized? Through an extensive systematic literature review, we identified 24 commonly utilized contextual variables across existing HRSs. To provide a structured approach for understanding, we organized the variables with a framework that classifies contextual variables into four distinct categories: objective-static, objective-dynamic, subjective-static, and subjective-dynamic. Our findings highlight the diverse yet uneven distribution of these variables within the framework, emphasizing the need for a balanced consideration of both objective and subjective data in developing comprehensive HRSs. The proposed framework serves as a robust foundation for future advancements, aiming to enhance the personalization capabilities of HRSs and ultimately improve health outcomes.

Keywords

Health Recommender Systems, Personalized Medicine, Contextual Variables, Data Categorization, Context-Aware Systems

1. Introduction & Background

Noncommunicable diseases (NCDs), including diabetes, obesity, and cardiovascular diseases, represent the leading cause of mortality, contributing to 74% of deaths worldwide [1, 2]. A substantial number of these deaths are linked to lifestyle choices, with over 20% being related to dietary habits, such as the consumption of sugar-sweetened beverages, which elevate metabolic risks [3]. Preventing NCDs and related deaths requires individuals to adopt lifestyle changes [4].

Previous studies have shown that personalized mobile health interventions can be an effective approach for facilitating habit formation and, consequently, promoting lifestyle changes in individuals [5]. The effectiveness of these interventions is largely driven by their ability to tailor recommendations to the individual, a capability often enabled by Recommender Systems (RSs) [6, 7, 8, 9].

These personalized recommendations are achieved through a comprehensive understanding of the user, informed by the contextual variables collected by the system. This precise tailoring enhances the relevance of the recommendations to the individual user, leading to higher user engagement. As a result, there is a greater likelihood that the user will adopt the recommended behavior changes into daily life, fostering healthier habits and ultimately contributing to the prevention of NCDs [10, 11].

Health Recommender Systems (HRSs) serve as a prominent example of personalized (mobile) health interventions. The effectiveness of HRSs is closely tied to their ability to deliver personalized recommendations tailored to the individual user [12, 13]. Therefore, it is crucial to examine the contextual variables that these systems collect to enable such personalization [11, 14]. Understanding which variables are gathered and how they are utilized can provide valuable insights into the factors that drive

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the accuracy and relevance of recommendations. This research investigates the contextual variables currently employed by HRSs and, hence, addresses the following research questions 1:

RQ1: Which contextual variables are currently used in HRSs?

Furthermore, we aim to gain deeper insights into the role and relevance of these variables for personalized recommendation in general, as well as, for specific health goals such as improving mental health or sleep as well as weight loss. This endeavor is reflected in RQ2:

RQ2: How can the currently used variables be categorized?

To answer RQ1, we conducted a systematic literature review, identifying 24 commonly utilized contextual variables within the existing HRSs landscape. To address RQ2, we propose a framework that classifies both existing contextual variables and those that may be identified in the future into four distinct categories. This framework aims to provide a structured approach for understanding and organizing the variables that influence the personalization capabilities of HRSs in general. For specific recommendation types, we further display the distribution of contextual variables for different recommendation types (e.g., healthy diet, mental health, sleep, weight loss).

2. Method

We conducted a systematic literature review in accordance with the PRISMA statement, complemented by a forward and backward citation search [15, 16]. The search strings for this systematic literature review were developed collaboratively by all authors. Key concepts central to the study, such as habits, health, personalization, and RSs, were identified, with a focus on contextual variables supporting healthier behavior change. These core concepts guided the selection of relevant terms, which were refined through multiple iterations to ensure comprehensive coverage of the literature. The final search strings, validated by all co-authors, were applied across PubMed, Scopus, and Web of Science—databases. Notably, Scopus was queried with two distinct search strings due to the initial search returning only two sources. The search strings and respective databases are presented in Table 1 of the online appendix.

The systematic literature review process was facilitated by the online tool CADIMA to ensure reproducibility [17, 18].

The review exclusively incorporated peer-reviewed, open accessible English-language journal articles, conference proceedings, and detailed project descriptions. Studies that did not investigate RSs, did not personalize recommendations or suggestions in a health-related or habit-changing context, or did not indicate input variables were excluded. The context was considered health-related if it encompassed promoting physical, mental, or emotional well-being. Habit-related contexts were defined as those aiming to influence or modify behaviors and routines to improve overall health outcomes.

A graphical representation of the literature selection process is shown in Figure 1. In total, n = 414 results were obtained (391 after duplicate removal) and initially screened based on the title, abstract, and exclusion criteria mentioned above. After the full-text screening, 48 articles were considered eligible. Among the 48 sources, seven were identified via PubMed, two via Scopus, and eleven via the Web of Science database. Consequently, 48 articles were finally included in the review. From these articles, 267 variable instances were identified. These instances denote individual mentions of a variable; for example, the variable "Age" might be cited multiple times across different papers, with each occurrence contributing to the total of 267 instances. Consequently, 24 unique variables were extracted.

Following the systematic literature review, the authors organized the identified variables into the framework, presented in Figure 2, which comprises four distinct categories. Moreover, the authors classified the identified papers from the literature review into eight distinct categories based on their application. The initial categorization of variables and papers was conducted by one author, after which the other authors reviewed it, leading to a multilateral discussion that refined and finalized the categorization.

Figure 1: Systematic Literature Review Flow Diagram

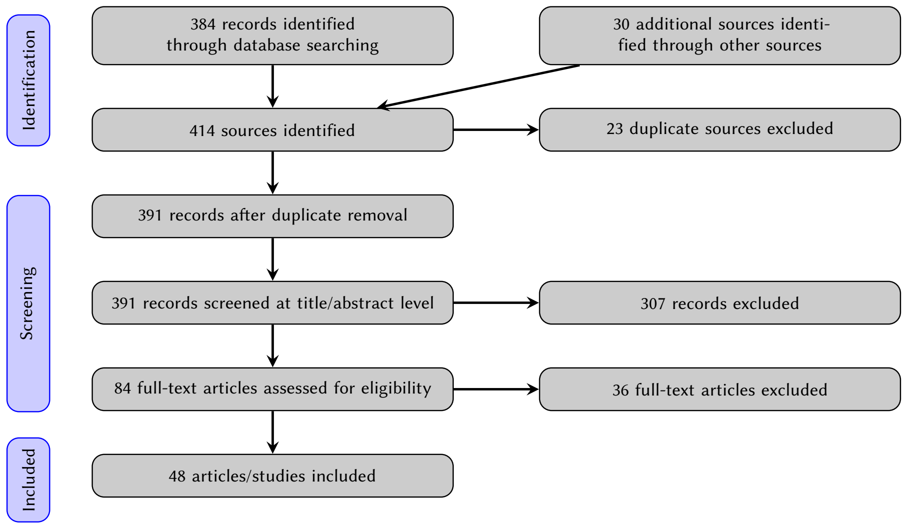
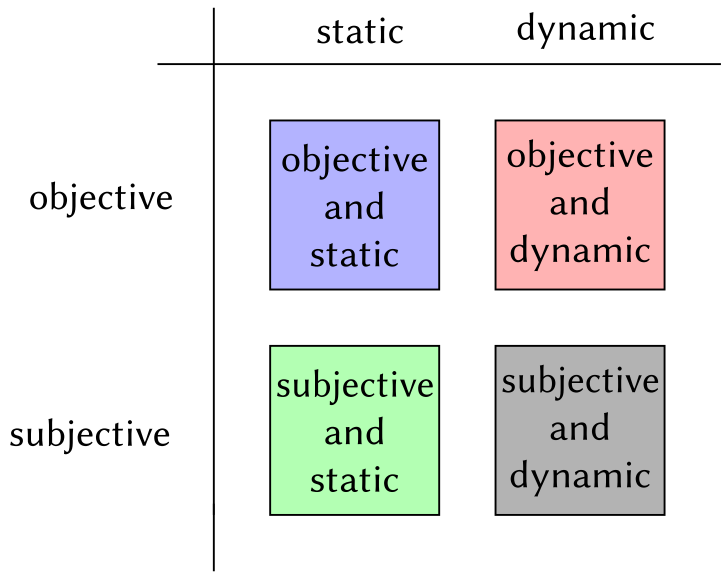


Figure 2: Framework for Structuring Data Collection in HRSs Development



3. Results

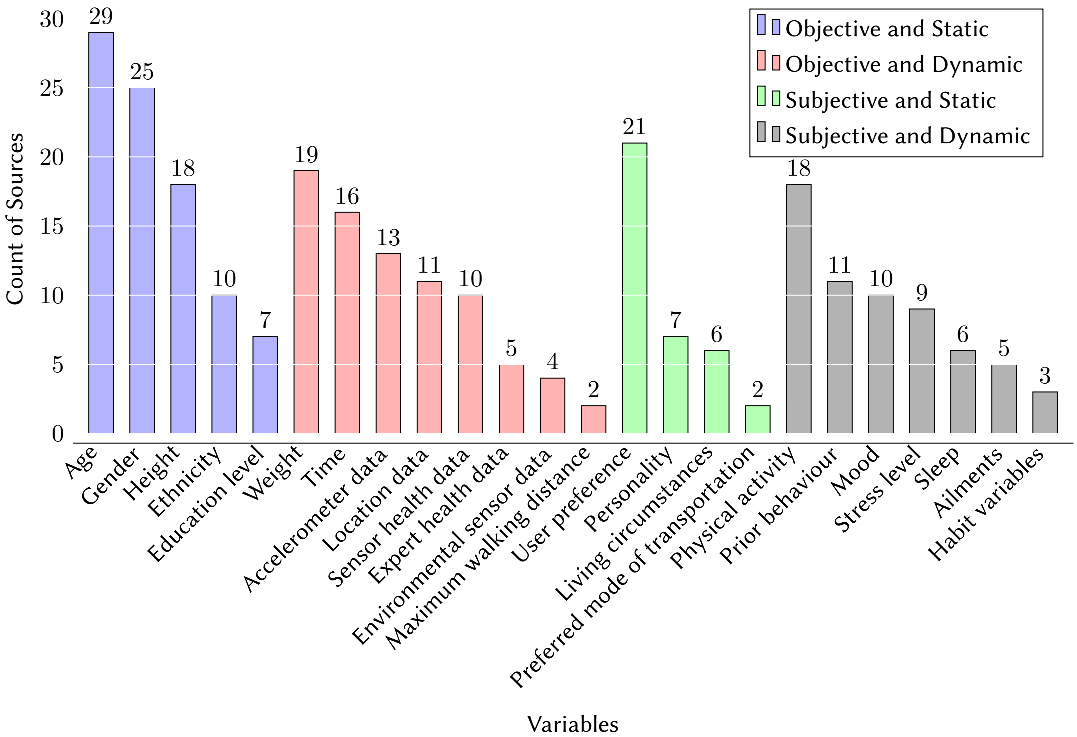
To facilitate a straightforward analysis, the authors propose a framework delineated by two principal axes: "objective-subjective" and "static-dynamic". This segmentation builds upon previous unidimensional approaches used to organize variables for HRSs, extending them into a second dimension to provide a more nuanced categorization [19, 20]. The vertical axis is grounded in the work of [19], who categorized data collection mechanisms into passive and active sensing, which can be adapted to the objective subjective spectrum. Objective data, such as accelerometer readings, is gathered without direct user input, while subjective data captures users' feelings or opinions, which are not directly measurable as external inputs. The horizontal axis of the framework draws on the concept of temporal context introduced by [20], distinguishing between static and dynamic variables. For instance, variables like gender may remain constant, while others, such as a user's weight, can vary over time. The colors chosen in Figure 2 symbolize the same categories as depicted in Figure 3.

The framework distinguishes between four different categories of contextual variables: First, there is *objective and static*, which includes quantifiable and unchanging variables, such as gender or ethnicity.

Second, *objective and dynamic* refers to quantifiable variables that fluctuate over time, like weather data or measurements from health sensors, such as smartwatches. Third, *subjective and static* encompasses personal and consistent preferences or perceptions, such as personality traits. Finally, *subjective and dynamic* involves personal factors that are both individual and variable, including mood or current stress levels. We have classified the variables into five within objective and static, eight within objective and dynamic, four within subjective and static, and seven within subjective and dynamic.

In Table 2 of the online appendix, the 24 distinct variables identified from the systematic review and the frequency of occurrence across the 48 analyzed papers are displayed. The frequency of variable references varies as shown in Figure 3, with "Age" being the most frequently cited variable at 29 references, whereas "Preferred mode of transportation" and "Maximum walking distance" are the least cited with only two references. This diversity in variables encompasses a broad spectrum, ranging from demographic data and physical conditions to mental and emotional states, as well as environmental data such as weather conditions measured by environmental sensors. This highlights the extensive and multifaceted nature of the data considered in HRSs.

Figure 3: Presence of Variables for HRSs in Literature



The heatmap in Table 1 illustrates the distribution of variables across different recommendation types. Each entry in the table represents the absolute frequency with which a particular variable is considered for a given recommendation type, with darker shades indicating higher frequencies. Additionally, the percentage column displays the proportion of each recommendation type relative to the 48 analyzed papers.

Table 1 reveals several insights. Firstly, the majority of sources fall within the categories of physical activity recommendations or the broader domain of dietary recommendations. As expected, variables closely tied to specific recommendation types, such as "Physical activity" reported by the user, are most commonly found in their corresponding RSs. Interestingly, however, variables that do not have an obvious connection to a particular recommendation type are also utilized across various recommendation types. For example, variables that measure a user's stress level are utilized not only in mental health and stress management RSs but also in physical activity and weight loss recommendations, as stress levels can directly impact a user's weight [21]. Secondly, some variables appear to be more prominent

Table 1
Distribution of Recommendation Types

Recommendation Type	Percentage	Variables																							
		Accelerometer data	Age	Ailments	Education level	Environmental sensors	Ethnicity	Expert health data	Gender	Habit parameters	Height	Living circumstances	Location data	Maximum walking distance	Mood	Personality	Physical Activity	Preferred mode of transportation	Prior behaviour	Sensor health data	Sleep	Stress level	Time	User preference	Weight
Healthy Diet and Physical Activity Promotion	8.33%	0	3	1	1	1	1	0	3	0	4	1	1	1	0	0	1	0	1	0	1	0	1	4	4
Healthy Diet	8.33%	0	3	2	0	0	1	1	3	0	2	0	0	0	0	1	1	0	0	1	0	0	0	2	2
Healthier Lifestyle (Unspecific)	8.33%	0	3	0	1	0	2	1	3	1	1	1	0	0	0	2	1	0	1	1	0	0	2	3	1
Mental Health & Stress Management	25.00%	4	3	0	2	1	1	1	3	1	0	0	5	0	6	2	1	0	3	4	3	7	6	2	0
Physical Activity	27.08%	6	8	2	2	1	3	1	6	0	5	2	3	0	4	2	8	2	2	0	0	1	4	4	6
Smoking Cessation	8.33%	0	4	0	0	0	1	1	4	1	1	2	1	0	0	0	1	0	2	1	0	0	0	3	1
Sleep	4.17%	1	0	0	0	1	0	0	0	0	0	0	1	1	0	0	2	0	1	2	1	1	1	1	0
Weight Loss	10.42%	2	5	0	1	0	1	0	3	0	5	0	0	0	0	0	3	0	1	1	1	0	2	2	5

overall. For example, "Age" and "Gender" are consistently important across all categories, while "Stress level" is particularly prevalent in mental health and stress management RSs.

4. Discussion

There is considerable variation not only in the number of contextual variables employed across different sources but also in the way these variables are utilized. A prominent observation is the preference in current HRSs for collecting objective rather than subjective data. Objective variables represent 169 out of the 267 variable instances, accounting for 63.3%. This preference likely stems from the relative ease of collecting objective data. For instance, when acquiring accelerometer data, timestamps are often included and can be obtained with minimal effort, whereas collecting data on a user's personality may necessitate substantial resources, such as administering comprehensive questionnaires [22]. This trend is corroborated by the findings of [23], who also noted a diminished use of variables associated with mental health in HRSs, pointing to a potential gap in the integration of psychological and emotional factors. In particular, the integration of subjective data beyond the user's preferences and prior behavior is comparatively scarce. These subjectively collected factors are, however, essential for personalizing recommendations to align with individual mental states and are difficult to objectively collect via sensors.

Yet, there is a discernible increase in efforts to integrate subjective measures, particularly psychological variables, into RSs. Notably, initiatives such as Zenspace and Studentlife have pioneered the incorporation of mental health metrics into their platforms [24, 25]. Additionally, the study by [23], which includes a personality measure within their RS, underscores a growing trend toward the adoption of subjective data in these systems.

The analysis further indicates a wide-ranging but imbalanced use of variables in the literature, emphasizing the necessity of comprehensive inclusion in HRSs. The prevalence of certain variables points to their perceived importance and utility in the field, while the less frequently cited variables may represent opportunities for innovation in HRSs research and practice. Given this context, our proposed framework offers a practical step for researchers to evaluate and enhance their HRSs. By assessing the variables they currently use against the framework's categories, researchers may realize that they are predominantly utilizing variables from a single category. This awareness encourages them to reconsider their variable selection, exploring the inclusion of variables from other categories that could be beneficial. For example, an HRS that primarily relies on objective, static data might be significantly improved by integrating subjective or dynamic variables, thereby capturing a more comprehensive picture of the user's context. This approach not only enriches the personalization capabilities of the system but also addresses the identified imbalance in variable utilization, contributing to the development of more effective and user-centric HRSs.

5. Limitations

Not all 24 identified variables are likely to be equally essential for improving the quality of recommendations. A similar conclusion was reached by [26], who distinguished between various observed contextual features in their study. Variables that do not improve the quality of recommendations can complicate compliance with privacy regulations and increase the burden on users (e.g., due to repetitive subjective assessments), ultimately leading to inefficiencies. It also increases the demand for computing power, particularly when the HRS runs on a local device, and heightens the risk of data breaches. Therefore, there is a clear need to adopt a more judicious approach to data collection [27]. This cautious stance is critical to ensure compliance with legal standards and to protect individual privacy, particularly when it is uncertain whether the collected data will provide significant utility for the application or study. This guideline acts as a safeguard, suggesting that data should only be gathered if it is both essential for the intended purpose and can be securely managed.

Moreover, the variables identified in this study are not exhaustive and vary widely in their definitions and applications, which could affect the generalizability of the findings. For example, the variable "Time" can be recorded in various formats, such as absolute (e.g., "8 AM") or relative (e.g., "after lunch"). This variability may lead to inconsistencies in how data is interpreted across different systems. Similarly, subjective variables like "Personality" could yield different results depending on the used scales, affecting the comparability and reliability of the data collected.

Furthermore, the distinction between static and dynamic variables in health-related applications can vary based on the specific context and time horizon of the application. For example, weight may be considered a static variable in contexts involving habitual behaviors, such as reading or brushing teeth, where it is not expected to change significantly. In contrast, in applications focused on weight loss or fitness tracking, weight becomes a dynamic variable that changes over time. This demonstrates how the categorization is influenced by the time horizon and targeted outcomes of the application; longer time horizons can lead to more variables being classified as dynamic due to their potential for change. Finally, while variables such as gender and education level are often considered static due to their relative stability over time, they are not inherently unchangeable. Therefore, recognizing that these variables can also change suggests that distinguishing between variables that are generally static and those that are dynamic, depending on context and time horizon, could enhance the robustness of the framework.

6. Future research

The relevance of HRSs is expected to increase in the near future, particularly for applications in digital therapeutics [28, 19]. This is especially pertinent in light of upcoming regulations, such as the European Union's Artificial Intelligence Act, which will likely shape the development and implementation of AI-driven healthcare solutions.

One critical avenue for future research is determining which contextual variables contribute the most to effective recommendations for each HRS type. While our framework provides valuable insights and a structured approach for evaluating and categorizing variables, the specific impact of each variable on recommendation accuracy and user experience were not investigated. However, our categorization could provide a starting point for this deeper meta-analysis. Addressing this gap involves analyzing the effectiveness of individual variables across different HRSs to identify those that significantly enhance performance. This focus not only helps optimize the recommendation process but also prevents the unnecessary overcollection of information, thereby respecting user privacy and adhering to data minimization principles.

Another important focus for future work is understanding how these variables are currently measured and reported. Consistency and reliability in data collection are essential for the scalability and practical implementation of HRSs. Our review indicates that variables are measured using diverse methodologies, which can lead to inconsistencies and hinder comparability across studies. For instance, the variable "Personality" can be measured through various personality scales, each differing in relevance and predictive utility for HRSs outcomes. Conducting a comparative analysis of these measurement methods would help identify the most appropriate tools for data gathering. Establishing standardized measurement approaches would bridge the gap to the technological aspects of HRSs, facilitating the integration of these variables into system designs and promoting interdisciplinary collaboration. Likewise, our work may represent a further step toward the integration of HRSs into low-/no-code development platforms for mHealth applications. While first platforms emerged in recent years, providing generic mechanisms for easily developing (self-)adaptive interventions is still an underexamined aspect [29, 30]. By identifying important variables in HRSs across different health domains, our work may provide further guidance in this regard. In summary, future research should focus on pinpointing the key variables that most significantly enhance recommendation effectiveness for each HRS type and on standardizing the methods used to measure and report these variables. This dual emphasis will improve the practical applications of HRSs and contribute to the ethical and secure management of personal health data. Ultimately, such efforts will advance the prevention and management of NCDs through more personalized, engaging, and effective health interventions.

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A. Online Resources

The online appendix for this submission can be found here.