Adaptive user interfaces in systems targeting chronic disease: a systematic literature review

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eHealth technologies have been increasingly used to foster proactive self-management skills for patients with chronic diseases. However, it is challenging to provide each user with the desired support due to the dynamic and diverse nature of the chronic disease. Many such eHealth applications support aspects of ‘adaptive user interfaces’ – that change or can be changed to accommodate the user and usage context differences. To identify the state-of-art in adaptive user interfaces in the field of chronic diseases, we systematically located and analysed 48 key studies in the literature with the aim of categorising the key approaches used to date and identifying limitations, gaps and trends in research. Our data synthesis, revolves around the data sources used for interface adaptation, the data collection techniques used to extract the data, the adaptive mechanisms used to process the data and the adaptive elements generated at the interface. The findings of this review will aid researchers and developers in understanding where adaptive user interface approaches can be applied and necessary considerations for employing adaptive user interfaces to different chronic disease-related eHealth applications.

CCS Concepts: • Human-centered computing → Graphical user interfaces; User interface programming.

Additional Key Words and Phrases: Adaptive user interfaces, Chronic disease, eHealth, Systematic literature review

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1 INTRODUCTION
Chronic diseases, such as stroke, obesity, cardiac care, diabetes and so on, have become one of the biggest challenges facing the healthcare system [53]. As reported by the WHO, chronic diseases account for 74% of fatalities each year [53]. Given a growing number of healthcare resources

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are devoted to chronic disease management, the medical care paradigm is shifting from hospital-based reactive treatment to long-term self-management [11, 48]. eHealth technologies have been increasingly used to foster proactive self-management skills and prevent the development of secondary complications through mechanisms such as digital education, self-monitoring, and feedback [14].

Many studies have demonstrated the value of eHealth technology in chronic disease management [41]. These technologies often focus on treating a specific disease and tracking key physiological indicators. However, people with chronic diseases vary greatly in their conditions, severity and human characteristics [23], with most being prone to secondary complications [11, 17] and their conditions are inherently long-lasting [23, 53]. Apart from that, many users have different age, physical and mental challenges, languages, educational attainment etc, all of which impact eHealth system usage [31]. To cope with this variability, some current eHealth applications take the context of usage into account, but some of them only apply predefined rule sets or fail to take into account the user’s unique traits and behavioural characteristics [18]. In this context, Adaptive User Interface (AUI) provides a viable solution to contextual variability [3] and an effective instrument for getting users continuously engaged and active, eventually leading to better physical and mental conditions [13, 18]. McTear [33] defines an AUI as “a software artefact that improves its ability to interact with a user by constructing a user model based on partial experience with that user”. A key goal of AUI is to take into consideration unique users’ perceptions so that they can use the system more effectively, with fewer errors and less frustration [31, 49, 52]. In this study, we present a systematic literature review (SLR) on the use of AUI in applications that target chronic diseases or risk factors corresponding to chronic diseases (RFCD).

Several literature reviews have been published on employing AUI for eHealth intervention [4, 15, 16, 37, 40, 44, 45]. However, they are mainly focused on a limited scope or specific techniques. Some reviews have a special focus on adapting to the emotional state, which is limited to discussing one factor that affects AUI change behaviour [4, 44]. Other reviews have examined specific application types, for example, Ambient Assisted Living (AAL) applications [45], physical activity coaching applications [37], applications using gamification [44] and rehabilitation applications [40]. Limitations of the scope thus disregard important investigations in other software domains.

In comparison to these review studies, this SLR explores the depth and breadth of evidence in AUI in the chronic disease domain, while employing a far more thorough and methodological analysis. In addition to discussing common adaptation components, this SLR goes beyond them by discussing 1) applications targeting chronic diseases or RFCD (e.g., unhealthy diet, harmful use of alcohol, physical inactivity and obesity), 2) target audience includes health professional and the general public which includes people with chronic diseases and those who wish to prevent from RFCD, 3) various proprieties that contribute to the user interface (UI) adaptation (e.g., who is responsible for adaptation and what is adapted in the UI), and 4) all types of software applications (e.g., web, mobile, desktop tablet applications).

The objective of this SLR is to provide a holistic view of the existing literature on the use of AUI in applications that target chronic diseases or RFCD and discover patterns and trends among various AUI. We organise our work around five major Research Questions (RQs) that can be directly linked to the objective of this SLR. To answer our RQs, we systematically identified and rigorously reviewed 48 relevant papers and synthesised the data extracted from those papers. We then created a taxonomy of our selected research papers that highlights important techniques and approaches characterised by the types of proposed AUI. The key contributions of this work are as follows:
A classification of adaptation data sources, data collection techniques, adaptive strategies, adaptation actors and adaptive elements for different AUI;

- Insights into the link between different adaptation proprieties and the connections between adaptation proprieties and specific types of applications;
- Provide empirical software engineering (SE) community with useful information about the evaluation of the AUI; and
- A list of key issues for future research efforts for advancing the state-of-the-art in supporting the creation and usage of AUI in the chronic disease domain.

The rest of this paper is organised as follows. We present the concepts of AUI used in the paper (Section 2.1) and the use of ehealth technology in the chronic disease domain (Section 2.2). This is followed by a discussion on the process of planning and conducting a SLR in Section 3. The result analysis for each RQ is presented in Sections 4, 5, 6, 7, 8 and 9. Section 10 reports a discussion of findings. The threats to validity are discussed in Section 11. Finally, we present our conclusions in Section 12.

2 BACKGROUND AND MOTIVATION

2.1 Adaptive user interfaces

The immediate point of contact between the user and their software is the UI. Therefore, it is crucial that users can easily communicate with the UI and understand the results provided by the UI [50]. The concept of making the UI design work for as many people as possible is promoted by several UI development methodologies, such as universal design and design for all [3]. However, a UI is not independent from its context of use which is defined in terms of the user, platform, and environment [6]. Users demonstrate differences in a variety of dimensions, therefore given solutions might demand users to modify their behaviour and problem-solving techniques in order to use the UI [36]. Additionally, the prevalence of smartphones offers new and flexible ways to interact with information, and various wireless sensors for tracking physiological parameters offer new possibilities for collecting contextual information [50]. As a result of context diversity and emerging opportunities, UIs developed for the fixed context of use type may no longer be sufficient. The adaptation of the UI provides a viable solution to contextual variability as it adapts to the context of use.

Depending on whether the system or end-user is accountable for the adaptation, there are three types of adaptation. a) Adaptability consists of allowing end users the explicit capacity to modify some aspects of the UI to make it suitable for their needs, which also refers to manual system in our review [3, 31], b) Adaptivity is the automatic adaptation of the UI in response to the changes of the context, which also refers to automatic system in our review [22, 39]. c) Note that the existing technologies mix both adaptability and adaptivity where the end-user and the system collaborate to achieve adaptation [4]. These technologies are known as semi-automatic systems in our review [34, 40]. Besides the three main types of adaptation, several particular forms of adaptation can be achieved with manual, automatic or semi-automatic systems. For example, personalisation, also referred to as customisation or tailoring, is a particular form of adaptation that typically targets the UI content [2, 3, 31]. Furthermore, a multi-targeting UI, or multi-platform UI, which facilitates functioning on different platforms and devices, focuses on the technical aspects of adaptation [6, 19]. Our focus in this review includes manual, automatic and semi-automated systems and particular forms of adaptations (e.g., personalisation and multi-targeting UI) used.
2.2 eHealth applications for chronic disease management

Chronic diseases, also known as non-communicable diseases (NCDs) [53], pose a major challenge to healthcare. The number of people with chronic diseases is steadily increasing, given that formerly lethal diseases are now regarded as chronic and also due to the ageing of the population [1]. Treatment for chronic diseases cannot be based solely on criteria, numbers and biological parameters [53]. Patients, therefore, are accountable for acquiring skills and techniques to learn to live with their disease, which is known as self-management [1]. There has been an increasing emphasis on developing technologies that can be applied to self-management. eHealth, for instance, encompasses a variety of technologies including computers, smartphones and wireless communications to provide access to health care providers and patients [48], which can also be used to foster medication adherence and improve self-tracking capabilities to aid in self-management [41]. Therefore, eHealth demonstrated promise in promoting health-related activities.

However, research demonstrates that individuals who seem to need eHealth the most, use it the least [20]. To scale up the deployment of eHealth applications, especially for patients with chronic conditions, these applications should be easy to use for all kinds of users. However, it is challenging to provide each user with the desired support due to the following three reasons. First, the chronic disease is a highly heterogeneous disease affecting patients differently (i.e., triggers, symptoms, severity varied) [23]. Therefore, patients may have diverse needs regarding self-management [21]. Second, the UI design should take into account the fact that the phases of chronic disease change over time [11, 17]. To avoid diabetes, for instance, a person could require certain self-management assistance, but once diabetes has formed, a different self-management routine would be required to cure it. Furthermore, chronic diseases are often co-morbid with other medical and/or psychopathological disorders [11], which leads to increased demand for healthcare and a much greater variety of user characteristics and functionality [17]. Third, the majority of chronic diseases are long-lasting, generally lifelong [23, 53]. Therefore, there is a need for the eHealth technologies to keep users engaged and motivated in the long run. Apart from diverse nature of chronic diseases, both health professionals and patients are individuals with diverse backgrounds, expertise and different demographical, psychological, and cognitive characteristics [31, 49]. The diverse and dynamic nature of users with chronic disease highlights the necessity of the AUI, which aims to improve the interaction between the user and UI by adapting UI to the users’ current goals and needs [3, 36]. Recent research has demonstrated the necessity of adaptability of eHealth technologies in facilitating chronic disease self-management [13, 18]. Offering these adaptations might enhance acceptance and motivation of eHealth applications usage [13, 20].

2.3 Prior Surveys and Reviews

The focus of our study is particularly on AUI in the chronic disease domain. This section reviews related secondary research, which includes SLR, systematic mapping and surveys, investigating the application of AUI. The scope and level of detail analysed in these studies of AUI vary. Prior to our work, there have been four existing SLR papers that discuss literature in a variety of areas related to AUI [4, 16, 40, 44]. Gonçalves et al. [16] presented a SLR of intelligent user interfaces (IUIs) in software systems based on the internet of things (IoT) or devoted to smart cities. However, the review is limited to discussing preliminary results and they did not publish the full paper. Two SLRs focused on a particular adaptation dimension, emotional state, which is limited to discussing one factor that affects adaptive interface change behaviour [4, 44]. In [40], the authors provided a thorough assessment of the literature on end-user adaptable technologies supporting rehabilitation. However, the authors emphasise the rehabilitation domain and most of the examined applications are customised by the therapists, without taking into account the role of patients.
Aside from the relevant SLRs stated above, two mapping reviews are also highly related to the work presented in this study [15, 45]. Hachey et al. [15] investigated web UI and their interaction with SE techniques. However, the authors placed an emphasis on technical aspects of the semantic web field, without exploring how users might impact the adaptation process. Sanchez et al. [45] undertook a thorough mapping of the state of the art in IUI research. However, as this study is focused on AAL technology, only a limited number of the literature is of interest to us. One existing survey [37] provided a thorough overview of the tools and methods currently being applied for tailoring in physical activity coaching applications and developed a tailoring model which encompasses seven tailoring concepts in the context of physical activity coaching. However, the tailoring model is intended to show how different tailoring concepts can be combined to adapt the motivational message instead of focusing on the UI adaptation.

3 RESEARCH METHODOLOGY

We followed the SLR guidelines and procedures in [27] and the work of [51] to uphold the integrity of our analysis and provide a reproducible process. One author first developed the review protocol and then it was reviewed by three authors to limit bias. Our protocol identifies the key objectives of the review, the necessary background, RQs, inclusion and exclusion criteria, search strategy, data extraction, and analysis of gathered data. Figure 1 depicts the whole process of our methodology, illustrating the three main steps of our review: SLR planning, selection and data extracting. These three steps will be covered in the following subsections.

3.1 Research Questions

Our goal was to develop RQs that would logically lead to the creation of a taxonomy of the surveyed research and address challenges when designing AUI in the chronic disease domain. The RQs of this study are as follows:
**RQ1:** *How AUI are being used?* It is necessary to understand what has been accomplished so far in terms of AUI for applications in the chronic disease domain. In this RQ, we examine the type of software used by the researchers, the type of solutions that have been proposed to address the related health conditions and what is the target user group of the proposed solution.

**RQ2:** *How are data being extracted, prepared, and used in the AUI?* The basic components of an AUI are defined by the data presented to a given application for the related adaptation [3, 6, 36]. When capturing data components, our goal is to obtain a taxonomy of the data used, how it is retrieved, and how this data correlates to different application domains. Considering the multifaceted nature of selecting, and extracting data, we dedicated two Sub-RQs to explore the use of data in AUI:

- **RQ2a:** *What type of data is collected to generate an AUI?* RQ2a investigates the many forms of data utilised in AUI. Given the large number of different applications that currently gather data from users, it is critical to understand the sorts of data that are being analysed.
- **RQ2b:** *How is this data being extracted/colllected?* RQ2b examines how data can be extracted and processed. Furthermore, data capturing techniques are frequently reliant on the sort of data that the application seeks to extract, which aids in discussing the relationship between data collection techniques and the data obtained.

**RQ3:** *What are the adaptive mechanisms used in generating the AUI?* The adaptive mechanism typically consists of *adaptive strategy* (what strategies are exploited to drive the adaptation?) and *adaptation actor* (who initialises the adaptation?). This RQ aims to explore the decision-making process for changing the AUI. Considering the aspects of the decision process that will be studied, we investigate RQ3 by means of two Sub-RQs:

- **RQ3a:** *What types of adaptive strategies are used to generate the AUI?* RQ3a explores the different adaptive strategies used to change the UI. We also look at common adaptive strategy pairings and how adaptive strategies are selected for various applications.
- **RQ3b:** *Who is adapting the UI?* RQ3b examines the different adaptation actors that trigger the adaptation process. We also investigate the interaction between the adaptation actors, adaptation strategies and corresponding applications.

**RQ4:** *What are the adaptive elements used in the AUI?* This RQ investigates what adaptations are executed in different applications. We want to obtain a taxonomy of the adaptive elements used, the frequent combinations of adaptive elements, and how the adaptive elements are associated with different application domains. Our goal is to inspire researchers on how to use multiple adaptive elements in useful ways and match particular adaptable elements to appropriate applications.

**RQ5:** *How are the studies that employed AUI developed and evaluated?* This RQ investigates and reports the design and evaluation approaches used by the included primary studies. In particular, we analyse the evaluation approach, evaluation indicators and evaluation results of the primary study. In addition, the results of this RQ are correlated with applications in order to present the trends of evaluation approaches and indicators for different types of applications. The results of this RQ will help the SE community understand which factors in the evaluation process are under-described or overlooked, thus making it difficult to validate the proposed solutions.

### 3.2 Search strategy

Our search strategy was intended to identify and collect all literature that complies with the inclusion and exclusion criteria detailed in Section 3.3. A mixed search strategy is adopted, with both automatically searching through electronic databases and manually searching through conference and journal proceedings.
3.2.1 **Data sources.** We surveyed and screened the search engines used in previous literature reviews in SE [32, 46]. The list of electronic databases we eventually decided to search were: ACM Digital Library, IEEExplore, Springer link, ScienceDirect, Scopus and Medline. Wiley, Compendex, and Inspec were excluded due to their high overlap with other search engages. Compendex and Inspec overlap highly with Scopus [32]. Wiley is indexed by Scopus [54]. We faced certain difficulties when conducting the search. First, the SpringerLink search engine does not support title, abstract and keyword searches at the same time. We either needed to search for the full text of the article or the title only. The former yielded 61,722 papers, while the latter strategy, in contrast, only returned 4 papers. To address this issue, we followed the approach used in [32] and included the top most relevant 2,000 papers returned by the full-text search. Another challenge was the limited number of search terms allowed in Science Direct, which demands splitting the search string into multiple search strings. Finally, digital libraries like ACM, IEEE, and Medline cannot simultaneously provide the ability to limit searches to multiple specific areas, e.g. title, abstract, and keywords combined. Besides, Scopus can be used as a complement to other databases because it indexes the majority of SE articles and conferences [28].

3.2.2 **Search terms.** PICOC criteria [27] were used to determine the search terms, shown in Table 1. Instead of searching for specific chronic conditions, we employed broad phrases from the health domain for two reasons 1) working with too many search terms might be challenging in some databases (e.g., ScienceDirect) 2) exhausting chronic disease search terms in automated searches is hard. The chosen search terms have been modified and refined to fit each search engine since the chosen digital libraries have different constraints and their own unique search syntax. Based on all the identified search terms, several rounds of trial searches were carried out on six online databases. We randomly picked 10 papers from each database to verify that the obtained list of studies were the most relevant for our review.

| Concepts      | Major search terms                                                                 |
|---------------|------------------------------------------------------------------------------------|
| Population    | (Application OR smartphone OR "smart phone" OR "cellular phone" OR "cell phone" OR cellphone OR software OR android OR ios OR windows OR tablet OR iPad) |
| Intervention  | (adapt* OR tailor* OR flexible OR personali?e* OR customi?e* OR context*-aware*) AND (GUI OR interface OR UI OR "user experience" OR UX OR usability) |
| Context       | (health OR healthcare OR ehealth OR mhealth OR disease? OR disorder? OR illness* OR patient?) |

3.3 **Inclusion and exclusion criteria**

It is important to note that certain studies do not offer the necessary information to find the answer to the questions posed in the present investigation. The inclusion and exclusion criteria were applied to all retrieved studies from databases and target venues at different steps.

- **I01:** Full-text papers published as journal or conference papers that focus on AUI in eHealth applications targeting chronic disease.
- **I02:** Entire papers are written in English and use academic literature references.
- **I03:** Study must be available in full text and published in a renowned digital library.
- **E01:** Gray literature, Workshop articles, posters, books, work-in-progress proposals, keynotes, editorial, secondary or review studied.
- **E02:** Short papers less than four pages, irrelevant and low-quality studies that do not contain a considerable amount of information for AUI to extract.
3.4 Study Selection

Figure 1 shows the number of studies retrieved at each stage of this SLR. The selection of primary research was performed using predetermined inclusion and exclusion criteria (see Section 3.3). From the first stage to the final screening, the essential records of the papers were kept in excel spreadsheets and the Mendeley library. Separate sheets were kept in Excel to keep track of the selection decisions for each phase. By adopting these techniques, the consistency of the inclusion and exclusion criteria can be verified. The selection process is effectively divided into four phases:

Phase 0: We ran the search string on the six digital libraries and retrieved 7,145 papers after removing the duplicates.

Phase 1: Publications found during the initial search were assessed for their suitability based upon analysis of their title and abstract. Studies were then transferred to the next round of screening for further investigation if it was not possible to decide by reading the titles and abstract. At the end of this phase, 310 papers were selected.

Phase 2: Publications selected during Phase 1 went through a more thorough analysis (by skimming the introduction, methodology and results). 23 papers were chosen as a random sample and were reviewed by two co-authors. Two co-authors and the first author agreed on the study selection in over 75% of the studies. Disagreement was easily resolved through discussion with the third author. As a result, 57 papers were later included. Then we applied both backward and forward snowballing techniques [55] and found a total of 18 potentially relevant papers (See Section 3.4.1). This phase resulted in 75 papers.

Phase 3: Publications selected during Phase 2 were engaged in full-text screening. We excluded several papers beyond the planned scope and do not provide sufficient data to answer our RQs. At the end of Phase 3, we selected 48 papers for review.

3.4.1 Snowballing. In order to complete the selection of articles, a manual search was conducted in Phase 2 according to the guidelines presented in [55]. It should be noted that we carried out the snowballing after Phase 2 rather than Phase 3, primarily to acquire more relevant studies. Figure 1 depicts the whole process of snowballing. Google Scholar is used to conducting the forward snowballing by identifying additional papers that cited any of the included studies and backward snowballing through scanning the references of the selected papers in Phase 2. We believe that this manual search phase was necessary in order to reduce the risk of relevant literature being lost due to automated searches. We identified 145 potentially relevant papers by paper title in the reference list from 57 included papers. In the end, 14 articles were left after applying inclusion and exclusion criteria, removing duplication and full-text screening, bringing our total number of primary studies to 48.

3.5 Study quality assessment

Each publication in the final set was assessed for its quality. The quality assessment (QA) procedure occurs at the same time as the extraction of relevant data and has the aim of ensuring that a particular study’s findings will make a valuable contribution to the SLR. A set of study quality assessment questions are listed in Table 2. These questions are adopted and adjusted from [27]. Each paper was categorised on a score of 1 to 3 (low to high) by answering the QA questions.
Table 2. Study quality assessment questions

| # | Quality assessment questions                                                                                                                                                                                                 |
|---|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| QA1 | Are the aims and objectives of the study clearly specified?                                                                                                                                    |
| QA2 | Is there an adequate description of the context in which the research was carried out?                                                                                                           |
| QA3 | Does the research design match the aims claimed for the research?                                                                                                                            |
| QA4 | Does the paper present a detailed description of the AUI employed?                                                                                                                            |
| QA5 | Is there a clear outcome and results analysis reported?                                                                                                                                       |
| QA6 | Does the paper provide limitations, summary and future work of the research?                                                                                                                  |
| QA7a | What is the quality of the venue where the study was published? Rated by considering the CORE 2021 [9] for the conference papers and ranking of conference and Journal Citation Reports 2021 [12] for the rankings of journal papers. |
| QA7b | What is the total number of citations for the paper?                                                                                                                                          |

3.6 Data extraction strategy
To answer RQ1–RQ5 and facilitate the data extraction process, we used the data extraction form in Table 3 to collect necessary information from the included studies. In this study, the data extraction procedure was divided into three phases.

**Phase 1:** A Google form was used for extracting data. We refined the questions and structure of the Google through three iterations by selecting one paper from each database and doing extractions.

**Phase 2:** After the questions and extraction form were finalised, the Google form was then sent to three co-authors for the same extraction on 6 papers. Then we did a comparison to check if there were any conflicting extracted information until all conflicts were resolved. Agreement of coded items before reaching consensus is quantified by using the percent agreement [25]. It is important to highlight that the agreement is only assessed for the most critical data (e.g. adaptive strategy, adaptive elements, etc.). Our overall percent agreement is 82% without an unusually high number of outlier scores.

**Phase 3:** After further discussion and consensus on the disagreements, the first author, under the close supervision of the second and third authors, re-extracted the data from the previously reviewed studies as well as the remaining 42 studies. The reliability of our data extraction method was also checked during the extraction process. In the case of finding recurrent disagreement concerning certain data, we adjusted the coding instructions accordingly. All extracted data were kept in a spreadsheet, which allows for quick reference while drafting the report.

Table 3. Data extraction form

| # | Questions | RQs |
|---|-----------|-----|
| 1-13 | Demographic data | 1. Paper ID, 2. Paper Title, 3. Authors of the Paper, 4. Venue, 5. First Authors affiliated university/institution, 6. First Author affiliated country, 7. The study population affiliated country in the paper, 8. Type of publication, 9. Publication Year, 10. Source Type, 11. Citations number, 12. Page number, 13. Study context |
| 14 | Information for paper | What are the major keywords of the study? |
| 15-21 | RQ1 | 16. What type of software application has been presented in the studies? 17. What type of solution is offered in the studies? 18. What health conditions have been targeted in the studies? 19. What is the target audience of the pap... |
| 22 | RQ2a | What environment data is collected to generate AUI for the application? |
| 23 | RQ2b | What user-controlled input data is collected to generate AUI for the application? |
| 24 | RQ2c | What techniques are being used to collect the data? |
| 25 | RQ3a | What are the adaptive strategies used in generating the AUI? |
| 26 | RQ3b | Who is adapting? |

Continued on next page
Table 3 – continued from previous page

| #  | Questions RQs                                                                 |
|----|-------------------------------------------------------------------------------|
| 27 | RQ4 What are the adaptive elements used in the AUI for applications?          |
| 28 | RQ5 28. What are the approaches to developing applications with AUI?          |
| 29 | 29. What are the types of models used in applications with the AUI?           |
| 30 | 30. Main outcome/ Results of the study?                                       |
| 31 | 31. How do they evaluate their results?                                       |
| 32 | 32. What approaches are used to evaluate the solutions?                       |
| 33 | 33. How are the evaluation results being measured?                            |
| 34 | 34. What is the length of time for the evaluation?                            |
| 35 | 35. What are the major recommendations of the study?                          |
| 36 | 36. What are the main limitations and main strengths of the study?            |
| 37 | 37. What are the key research gaps/ future work identified by each study?     |

3.7 Data Synthesis, and Taxonomy Derivation

We downloaded all the essential information in a data extraction sheet, including a) demographic data (e.g., title, authors, venue, affiliation and publication type), b) the answers for each RQ, c) the QA scores for all QA questions. Both qualitative and quantitative methods were used to synthesise the extracted data.

**Quantitative analysis:** We performed both univariate and multivariate frequency distribution analysis. The univariate frequency distribution offered a summary count of the occurrences within a particular variable. Multivariate frequency analysis was used to aggregate the distribution of two or more variables to determine their interrelationships. We used Python and Microsoft Excel pivot table tools to build and visualise the cross-tabulation and other diagrams.

**Qualitative analysis:** To build our taxonomy on the use of AUI, we followed an open coding methodology consistent with constructivist grounded theory [7]. According to the advice of recent work within the SE community [47], we followed the two steps as detailed below: 1) we created the initial coding of data type, data collection technique and adaptive elements and 2) we selected categories from the most frequent or important codes we created and used them to categorise the data (focused coding). The initial coding was performed by one author and then refined during the focused coding process by two others until an agreement was made among all three. The results of these coding steps formed our taxonomy. This coding process is visualised in Figure 2.

![Fig. 2. Example of qualitative data analysis by using constructivist grounded theory](image-url)
4 OVERVIEW OF INCLUDED STUDIES

Here we provide an overview of the included studies with respect to demographics analysis and QA results. In Table 4, we provide an overview of these included primary studies with respect to their source of database. The highest percentage of relevant studies (10 studies, 21%) were found in Scopus. Although it is important to highlight that the largest number of relevant studies were found through snowballing (14 studies, 29%). We also report the distribution of the included studies related to the publication channel (i.e., academic, industry, etc.). Table 5 lists the 48 primary studies in our review.

| Digital library | Phase 0 | Phase 1 | Phase 2 | Phase 3 | % of all relevant studies |
|-----------------|---------|---------|---------|---------|--------------------------|
| ACM             | 653     | 72      | 11      | 6       | 13%                      |
| IEEE            | 645     | 57      | 10      | 5       | 10%                      |
| Medline         | 1523    | 45      | 6       | 5       | 10%                      |
| ScienceDirect   | 1273    | 29      | 5       | 4       | 8%                       |
| Scopus          | 1147    | 35      | 15      | 10      | 21%                      |
| SpringerLink    | 1913    | 72      | 10      | 4       | 8%                       |
| Snowballing     | 0       | 0       | 18      | 14      | 29%                      |
| All libraries   | 7154    | 310     | 75      | 48      | 100%                     |

Table 5. List of included articles

| Study ID | Title of paper                                                                 | Publication year |
|----------|--------------------------------------------------------------------------------|------------------|
| S1       | Tools for adaptation of a mobile application to the needs of users with cognitive impairments | 2021             |
| S2       | Pervasive multimedia for autism intervention                                   | 2012             |
| S3       | A Modular Mobile Exergaming System With an Adaptive Behavior                   | 2015             |
| S4       | Optimising engagement for stroke rehabilitation using serious games           | 2009             |
| S5       | Enabling Personalisation of Remote Elderly Assistant Applications              | 2017             |
| S6       | A Personalized Physical Activity Coaching App for Breast Cancer Survivors: Design Process and Early Prototype Testing | 2020             |
| S7       | Experience of Designing and Deploying a Tablet Game for People with Dementia   | 2017             |
| S8       | Move&Learn: an Adaptive Exergame to Support Visual-Motor Skills of Children with Neurodevelopmental Disorders | 2021             |
| S9       | “BelWell+: Multi-dimensional Wellbeing Monitoring with Community-guided User Feedback and Energy Optimization” | 2012             |
| S10      | "Improving the Efficacy of Games for Change Using Personalization Models"     | 2017             |
| S11      | A Mobile Rehabilitation Application for the Remote Monitoring of Cardiac Patients after a Heart Attack or a Coronary Bypass Surgery | 2009             |
| S12      | Designing Context Aware User Interfaces for Online Exercise Training Supervision | 2009             |
| S13      | Mobile@Old – An Assistive Platform for Maintaining a Healthy Lifestyle for Elderly People | 2017             |
| S14      | Dynamic Difficulty Adjustment with Evolutionary Algorithm in Games for Rehabilitation Robotics | 2016             |
| S15      | Personal health monitoring with Android based mobile devices                   | 2013             |
| S16      | A customizable mobile tool for supporting health behavior interventions        | 2007             |
| S17      | "A tailored, interactive health communication application for patients with type 2 diabetes: study protocol of a randomized controlled trial" | 2015             |
| S18      | MediNet: Personalizing the Self-Care Process for Patients with Diabetes and Cardiovascular Disease Using Mobile Telephony | 2008             |
| S19      | PEGASO: A Personalised and Motivational ICT System to Empower Adolescents Towards Healthy Lifestyles | 2014             |
| S20      | Intelligent interaction interface for medical emergencies: Application to mobile hypoglycaemia management | 2020             |
| S21      | Protecte: A mobile health application for the elder-caregiver monitoring paradigm | 2013             |
| S22      | User-tuned Content Customization for Children with Autism Spectrum Disorders | 2014             |
| S23      | Improving Mobile Device Interaction for Parkinson’s Disease Patients via PD-Helper | 2019             |
| S24      | generating context-awareness interface for medical applications               | 2011             |
| S25      | Adaptive User Interface for Healthcare Application for People with Dementia    | 2018             |
| S26      | Architecture of a System for Stimulating Intellectual Activity with Adaptive Environment SMILE | 2017             |
| S27      | Therapeutic Games’ Difficulty Adaptation: An Approach Based on Player’s Ability and Motivation | 2011             |
| S28      | Empirical Evaluation of Intelligent Mobile User Interfaces in Healthcare       | 2014             |
| S29      | Computerized decision support for beneficial home-based exercise rehabilitation in patients with cardiovascular disease | 2018             |
| S30      | Reconfiguration of Graphical User Interface                                    | 2011             |
| S31      | "Adaptation in serious games for upper-limb rehabilitation: an approach to improve training outcomes" | 2015             |
| S32      | EMERALD—Exercise Monitoring Emotional Assistant                               | 2019             |
Table 5 – continued from previous page

| Study ID | Title of paper                                                                 | Publication year |
|---------|--------------------------------------------------------------------------------|-----------------|
| S33     | Nourish Your Tree! Developing a Persuasive Exergame for Promoting Physical Activity Among Adults | 2020            |
| S34     | Adaptive Strategy for Multi-User Robotic Rehabilitation Games                   | 2011            |
| S35     | MPRL: Multiple-Periodic Reinforcement Learning for Difficulty Adjustment in Rehabilitation Games | 2017            |
| S36     | Move2Play: An Innovative Approach to Encouraging People to Be More Physically Active | 2012            |
| S37     | Enhancing the Physical Activity of Older Adults Based on User Profiles          | 2017            |
| S38     | Digital-Pheromone Based Difficulty Adaptation in Post-Stroke Therapeutic Games  | 2012            |
| S39     | Self-Adaptive Games for Rehabilitation at Home                                 | 2012            |
| S40     | Adaptive Gameplay and Difficulty Adjustment in a Gamified Upper-Limb Rehabilitation | 2018            |
| S41     | Usability of an Adaptive Computer Assistant that Improves Self-care and Health Literacy of Older Adults | 2008            |
| S42     | Adaptation of Graphics and Gameplay in Fitness Games by Exploiting Motion and Physiological Sensors | 2007            |
| S43     | Framework for personalized and adaptive game-based training programs in health sport | 2014            |
| S44     | Flowers or a robot army? (encouraging awareness and activity with personal, mobile displays) | 2008            |
| S45     | Fish’n’Steps: Encouraging Physical Activity with an Interactive Computer Game   | 2006            |
| S46     | Study of the Usability of an Adaptive Smart Home Interface for People with Alzheimer’s Disease | 2019            |
| S47     | Combined Health Monitoring and Emergency Management through Android Based Mobile Device for Elderly People | 2012            |
| S48     | Adapting Web-Based Information to the Needs of Patients with Cancer             | 2000            |

From these results, we find that a significant amount of research comes from academia, i.e., 73% of papers, followed by a small amount of research (17%) from industry-academic collaborations. There are limited studies that come from government initiatives (4%) and industry (6%). To date, most applications of AUI seem to be confined to academia. We also checked the included studies against the criteria for QA. In view of the QA results, it is concluded that most included papers established good objectives and context to present the research paper. The results also show that much effort has been put into the appropriateness of the way the research was designed to address the problem. One aspect still has room for improvement is the way studies describe the AUI. Another aspect to be improved is the outcome and result analysis reporting, in order to better validate the research results. Another point that should be improved is the findings, limitations, and future work statements in the studies, in order to better understand the presented approach. The following sections provide analysis and answers for our five RQs. The answers to all RQs, the existing SLRs and surveys found in the literature helped us develop the classification taxonomy (Section 10). Some classes in this taxonomy are not mutually exclusive, and each study can be inserted into one or more of them.

5 RQ1: HOW ARE AUI BEING USED?

This RQ explores the application of AUI in the chronic disease domain. Of the 48 papers we analysed for this SLR, most of the reviewed studies are from Canada (11%), followed by European countries (66%). Figure 3 provides a visual breakdown of how many chronic diseases we found within these 48 primary studies across a 21-year period. The distribution of papers collected over 2000 to 2021 was relatively evenly distributed with two minor exceptions (see Figure 3). There is very little work done between the years 2000 and 2007. This can be explained by the fact that the first introduction of smartphones to the market was in 2006 and the focus at that time was more on core ideas and concepts than the AUI [58].

It was not until 2012 that AUI became widely used in applications for chronic diseases, and the number of papers increased substantially, from one to six papers in one year. During this period, the set of target relevant chronic diseases also grew to become more diverse, including stroke, RFCD, ageing and autism. However, RFCD and stroke have remained the most active across the years. Out of the 48 research included, RFCD received the greatest attention (11 studies, 23%). RFCD is also the predominant study area before 2009. Although there seems to have been a decline in interest in AUI research after 2017, there are recent relevant studies which are included in this SLR.
5.1 Types of software application

A key finding in our literature study, which is also mentioned in other reviews [35, 40, 45], is that most AUI are available on mobile applications (18 studies, 57%) and web-based applications (14 studies, 29%) (see Table 6). The prevalence of web and mobile applications can be explained by their popularity and diverse user base. Creating AUI for the platforms with the largest usage makes the most sense. There is also a large number of papers that do not explicitly mention what type of application they proposed (11 studies, 23%). One study has both web and mobile versions of the application (S16). Very few studies proposed a tablet-based application (2 studies, 4%), desktop application (1 study, 2%) or bracelet application (1 study, 2%), which can be explained by the capability of these platforms. For example, a study that uses a bracelet application as the interface to communicate with the user might be hindered by screen size, thereby limiting the quantity and quality of information presented (S32).

5.2 Types of solution

We found that most of the papers developed a specific application. We classified these different solutions proposed in the study according to their primary focus. Four papers (S14, S27, S34 and S35), for instance, fall under the category of adaptive algorithms/techniques, although other studies also include algorithms/techniques when discussing the implementation phase. Some of these studies propose methodologies or frameworks for generating AUI (15%), and we classify these studies as ‘Approach’. One study proposes a specific tool to make the existing application adaptive (S5). The remaining 75% of studies propose specific types of applications. Among these studies, the health promoting and self-monitoring (HealPM) application (23%) is of the most frequent, followed by the game application (17%). The remaining articles are broken down into the following categories by application type: informative applications (6%); communication applications (2%); assistive applications (8%); rehabilitation applications (15%); and healthcare information management (HIM) applications (4%).

5.3 Type of target users

In the 48 studies, two main types of target users are identified, as well as the types of users to which the applications are adapted. It indicates that applications do not adapt to all types of users who use the app, which may depend on the user’s role and the task they perform through the application. As Table 6 shows, the first type is the general public who have chronic diseases or who are eager to prevent from RFCD. The other type is healthcare professionals who are responsible for overseeing, monitoring, or managing the health status of users. 46 studies (81%) targeted the general public
users. The remaining 2 studies are restricted to health professionals only. Additionally, we found 7 studies (15%) targeted both groups of users. Among them, four proposed solutions only adapt to the general public needs (S2, S13, S15 and S21). This can be explained by the role played by health professionals in these applications, who are mainly supervising and monitoring other users. As a result, there is less need for these applications to adapt to health professionals. It is also important to note that these applications are targeting different age groups of users (see Table 6). Although the target audience is an important part of developing AUI, the literature was scant on this matter. According to our findings, more than half (58%) of the articles did not report the target audience of the study. Older adults receive the most attention (13 studies, 27%). Of the remaining studies, three studies specifically targeted children, one study targeted adults, and one study targeted adolescents.

Table 6. How AUI are being used.

| Target users      | Adapting users | Study ID | Age group* | Type of software application* | Type of solutions |
|-------------------|----------------|----------|------------|-------------------------------|-------------------|
| General public    | General public | S1       | NS         | Mobile                        | Approach          |
|                   |                | S3       | NS         | Mobile                        | Application (Exercise game application) |
|                   |                | S4       | NS         | Desktop                       | Application (Rehabilitation application) |
|                   |                | S5       | Elderly    | Web                           | Tools             |
|                   |                | S6       | NS         | Mobile                        | Application (Health promoting and self-monitoring application) |
|                   |                | S7       | Elderly    | Tablet                        | Application (Therapeutic game application) |
|                   |                | S9       | NS         | Mobile                        | Application (Health promoting and self-monitoring application) |
|                   |                | S10      | NS         | Web                           | Application (Persuasive game application) |
|                   |                | S11      | NS         | Mobile                        | Application (Rehabilitation application) |
|                   |                | S14      | NS         | NS                            | Adaptive algorithm/technique |
|                   |                | S16      | NS         | Web & Mobile                  | Application (Health promoting and self-monitoring application) |
|                   |                | S17      | NS         | Web                           | Application (Informative application) |
|                   |                | S18      | NS         | Mobile                        | Application (Health promoting and self-monitoring application) |
|                   |                | S19      | Teenager   | Mobile                        | Application (Health promoting and self-monitoring application) |
|                   |                | S20      | NS         | Mobile                        | Application (Health promoting and self-monitoring application) |
|                   |                | S22      | Children   | Web                           | Application (Informative application) |
|                   |                | S23      | NS         | Mobile                        | Application (Assistive application) |
|                   |                | S24      | NS         | Web                           | Application (Healthcare information management application) |
|                   |                | S25      | Elderly    | Web                           | Application (Assistive application) |
|                   |                | S26      | Elderly    | NS                            | Approach          |
|                   |                | S27      | NS         | NS                            | Adaptive algorithm/technique |
|                   |                | S29      | NS         | Web                           | Application (Rehabilitation application) |
|                   |                | S31      | NS         | Tablet                        | Application (Rehabilitation application) |
|                   |                | S32      | Elderly    | Bracelet                      | Application (Healthcare information management application) |
|                   |                | S33      | NS         | Mobile                        | Application (Persuasive game application) |
|                   |                | S34      | NS         | Mobile                        | Adaptive algorithm/technique |
|                   |                | S35      | NS         | NS                            | Adaptive algorithm/technique |
|                   |                | S36      | Children   | Mobile                        | Application (Health promoting and self-monitoring application) |
|                   |                | S37      | Elderly    | NS                            | Application (Exercise game application) |

Continued on next page
Table 6 – continued from previous page

| Target users                  | Adapting users | Study ID | Age group* | Type of software application* | Type of solutions                                                                 |
|------------------------------|----------------|----------|------------|------------------------------|----------------------------------------------------------------------------------|
|                              |                |          |            |                              |                                                                                   |
|                              | S38            | NS       | Web        | Approach                     |                                                                                   |
|                              | S40            | NS       | Web        | Application (Rehabilitation  |                                                                                   |
|                              | S41            | Elderly  | NS         | Application (Assistive       |                                                                                   |
|                              | S42            | NS       | NS         | Approach                     |                                                                                   |
|                              | S43            | Elderly  | NS         | Approach                     |                                                                                   |
|                              | S44            | NS       | Mobile     | Application (Persuasive game  |                                                                                   |
|                              | S45            | NS       | Web        | Application (Persuasive game  |                                                                                   |
|                              | S46            | Elderly  | Web        | Application (Assistive        |                                                                                   |
|                              | S47            | Elderly  | Mobile     | Application (Health promoting |                                                                                   |
|                              | S48            | NS       | Web        | Application (Informative      |                                                                                   |
| Health professional          | S12            | Health   |            | Application (Rehabilitation   |                                                                                   |
| Health professional          |                | professionals |          |                              |                                                                                   |
|                              | S28            | Health   | Mobile     | Approach                     |                                                                                   |
| Health professional &        |                | General  |            |                              |                                                                                   |
| General public               | S2             | Children & Adult | Mobile | Approach                     |                                                                                   |
|                              | S13            | Elderly  | Web        | Application (Health promoting |                                                                                   |
|                              | S15            | Elderly  | Mobile     | Application (Health promoting |                                                                                   |
|                              | S21            | Elderly  | Mobile     | Application (Communication    |                                                                                   |
|                              | S8             | Children | NS         | Application (Exercise game    |                                                                                   |
|                              | S30            | NS       | Web        | Application (Healthcare        |                                                                                   |
|                              | S39            | NS       | NS         | Application (Rehabilitation   |                                                                                   |

* NS: not specified

6 RQ2: HOW ARE DATA BEING EXTRACTED, PREPARED, AND USED IN THE AUI?

In this RQ, we analyse the data types that are modelled and used by various AUI. The aim of our analysis is to understand the various types of data used, and how the data is collected/extracted. These perspectives can set the stage for future research and potential improvements in the effectiveness of developing AUI using different data sources.

6.1 RQ2a: What type of data is collected to generate an AUI?

An AUI needs to include a knowledge base. The triples that make up the context of use – user, platform, and environment – can be considered as aspects that facilitate AUI behaviour[3, 6, 36]. To analyse the types of data being used for generating AUI, we provided a high-level classification, along with descriptive statistics, as to how some types of data were used for a particular type of application. Table 7 provides an illustration of different data types used in all included studies. In our identified studies, we found two main types of data sources, namely environmental data and user data.

6.1.1 User data. User data is divided into three subcategories listed below:

User characteristics: Any system with an AUI must be able to characterise and distinguish between different end users [36]. In our identified studies, the most preferred user characteristics in generating AUI belong to the user’s physical characteristic (35%), user’s physiological characteristic
Table 7. Classification by type of data source of adaptation

| Data                         | Subcategories                  | Description (studies)                                                                 |
|------------------------------|--------------------------------|--------------------------------------------------------------------------------------|
| User characteristics         | User’s physiological characteristics (29%) | User’s health and normal functioning such as stress level, heart level, blood oxygen level. (S1, S3, S5, S11, S18, S20, S24, S27, S29, S32, S39, S41, S42 and S48) |
| (User data)                  | User’s physical characteristics (35%) | Physical capability and activity level of the user to perform different activities in daily life. (S5, S6, S9, S19, S21, S27, S33, S36, S43, S44, S45, S5, S4, S8, S18, S31 and S39) |
|                              | User’s psychological characteristics (8%) | Thoughts, feelings, and other cognitive characteristics that affect a person’s mood, attitude, behaviour, and functioning. (S5, S10, S12 and S43) |
|                              | User’s demographics (15%) | Quantifiable insights of users into the population such as age, gender, and computer literacy. (S1, S15, S17, S24, S26, S27 and S47) |
|                              | User’s preference (29%) | User preferred layout, input/output, theme, interface design. (S13, S16, S22, S23, S26, S30, S46, S17, S19, S21, S24, S25, S28 and S43) |
| Interaction related          | User’s social activity (4%) | The extent to which the user interacts with others around them. (S9 and S19) |
| (User data)                  | User’s performance in game (31%) | User’s performance in the game includes the scores, success and wins in the game. (S2, S4, S7, S8, S14, S27, S29, S31, S34, S35, S38, S39, S40, S42 and S43) |
|                              | User’s interaction with the interface (10%) | History of interactions (eg, click counting, visited, links, time spent, etc). (S14, S25, S13, S37, S46) |
|                              | User’s emotions (8%) | User’s emotion when interacting with the interface. (S17, S25, S32 and S37) |
|                              | User’s feedback (4%) | User’s feedback is collected in the form of questions and answers, or by non-direct methods. (S6 and S11) |
| Task specific (User data)    | User’s role (4%) | User’s role is a predefined category assigned to users based on their job title or some other criteria. (S24 and S28) |
|                              | User’s goals (4%) | User’s goals are the end state(s) that users want to reach. (S12, S29 and S44) |
|                              | User’s motivation (6%) | User’s motivation is what arouses and sustains action toward a desired goal. (S5, S12 and S34) |
| Environmental data           | Device types (2%) | The interface will adapt different devices user used. (S18) |
|                              | Operating Platform (2%) | The interface works across platforms. (S13) |
|                              | Environmental condition(s) (4%) | The interface will adjust e.g. brightness level based on the time of the day and location. (S12 and S28) |
|                              | Display sizes (6%) | The interfaces will adapt to different display sizes providing the best view to the users. (S12, S13 and S25) |

(29%) and user’s preference (29%), respectively. For example, regarding the physical characteristics, the user’s physical baseline level (weight, height and physical limitations) or actual physical activity level is used for difficulty adjustment for exercise (S3, S4, S5 and S6) or game (S27 and S8), customising a training plan (S21 and S39) or changing the graphic design as a motivation for sustaining physical activity (S19, S33, S36, etc.). Heart rate data (S3, S5, S11, etc.), medication treatment (S18), blood glucose level (S20), health impairments (S1 and S18), disease details (S27, S24, S39, etc.), the oxygen level in the blood (S42) are the physiological data addressed in the articles we included.

The remaining identified subcategories of user characteristics belong to user’s demographics (15%), user’s psychological characteristics (8%) and user’s social activity (4%). Studies primarily employed data on users’ cognitive features (S5, S12 and S43) and personality factors while examining psychological characteristics (S10). In terms of demographic characteristics, researchers mostly employ age (S1, S24, and S27), gender (S27), and literacy data (S15, S17, S24, S26 and S47). Each of these subcategories specifies one dimension of the user characteristics. This paper also investigates in terms of the variety of dimensions used for user characteristics data. Our analysis revealed that over 80% of included articles used at least one of the above-mentioned user characteristic subcategories; a number of articles (29%) applied more than one subcategory of user characteristics to achieve a higher understanding of users.
**Interaction related:** In addition to the user characteristics data, an AUI must be able to track the interaction between the user and the interface if it is to provide the help that is appropriate for the context and the specific user [3, 6, 36]. We found that *user’s performance in the game* (31%) is the most common form of subcategories under interaction related data. The remaining subcategories are divided into *user’s interaction with the interface* (10%), *user’s emotions* (8%) and *user’s feedback* (4%). Various dimensions used for interactively related data are also investigated. The results show that about half (48%) of the included articles used at least one of the above interaction-related subcategories. Five articles (8%) applied data from multiple interaction-related subcategories to capture the complexity of the interaction.

**Task specific:** Users may specify their roles associated with particular responsibilities, factors that motivate them, and goals they want to achieve with the application, or rely on the system to infer. We categorise task-related data into the three categories: *user’s roles* (4%), *goals* (4%), and *motivations* (6%). In our identified studies, 6 (12%) articles used at least one of the above task-specific subcategories; only one article (2%) applied two categories of task specific data.

**Environmental data.** In addition to the data from the user, the adaptive system should learn about itself. The system should be aware of the physical devices (e.g., phone, tablet, laptop, etc.), operating systems and different types of the software application (e.g., web, desktop, rich Internet application, etc.) [3, 6]. At the same time, the environment in which the device is located also forms the usage context, and we collectively refer to the above knowledge of the system itself as environmental data. However, few studies mention that they have been adapted to environmental data. Some environmental data such as *device type* (S18), *operating platform* (S13), *environmental conditions* (S12 and S28), and *display size* were introduced in some of the included studies (S12, S13 and S25).

**Coupling user data.** Among the studies we identified, we find that the majority of adaptive systems (58%) use only one type of user data. Among the studies with one type of user data, around 75% of the studies used data only related to user characteristics. The remaining 25% of the studies had only one source of user data and targeted the interaction between the user and the interface. In terms of the variety of dimensions used, a significant number of articles (42%) used more than one type of user data to achieve a higher understanding of users. For the studies that employ multiple user data, 16 articles (30%) that have adapted to user characteristics, interaction related have also been covered. For subcategories under each type of user data, *user’s physical characteristics* data and *user’s performance in the game* is the most common combination between user characteristics and interaction related data (12%). On the other hand, in 10% of cases, *user characteristics* are accompanied by *task specific* data which itself came with *interaction related data* in 4% of the cases. The combination of *user characteristics* and *interaction related data* seems to be the most used approach in user profiling. In all included studies, *task-specific* data is not used alone.

**User data and application types.** Along with the discussion around user data, it’s critical to comprehend how user data relates to the specific application. Figure 4 shows a bubble chart of various types of user data according to the application to which they are applied. The frequency of a certain combination of categories is indicated in each bubble. However, unlike previous review studies [4, 40, 45], we added a third dimension to our bubble charts: a legend with a colour scale that indicates the average study quality score of all papers in a given bubble. Examining this figure, we found that the *user characteristics* category is the preferred type of user data used in all kinds of proposed applications, particularly in the application of rehabilitation and HealPM applications. Interaction related and task specific data has a similar pattern as user characteristics.
6.2 **RQ2b: How is this data being extracted/collected?**

In RQ2b, we investigate data collection techniques to collect and extract user data. The answer to this Sub-RQ leads to the definition of a taxonomy based on the data collection technique (See Figure 5). Aranha et al. [4] classify the data collection techniques into two categories: based on **visible inputs** and based on **invisible inputs**. Visible inputs are those that can be observed with the naked eye without the aid of a computer or other technical resources. In turn, invisible input based techniques mainly analyse signals and electrical impulses, leading to the use of specific sensors.

### 6.2.1 Data collection techniques based on visible input

This category does not require direct contact with sensors to collect user data. In general, visual input is collected by asking the user to answer
Adaptive user interfaces in systems targeting chronic disease: a systematic literature review

some questions or by allowing the user to manually change settings and preferences while using the application at a later time. Among the studies that use visible input in our SLR, user input through application was by far the main visible input for collecting all types of data, with 30 studies (63%) using this approach. Questionnaires (S2, S5, etc.), manual user configuration settings (S4, S13, etc.), and manual user input health or physical information (S6, S18, etc.) are all examples to collect user input through the application. Another way to use visible input is to use user behaviour data, which accounts for 27% of the included studies. Examples of common forms of behaviour data analysis include examining phone usage (S9, S13, etc.) and user game performance (S7, S8, etc.). Two studies obtained user information based on activities with a mouse and keyboard (S31 and S38).

6.2.2 Data collection techniques based on invisible input. Apart from the visible input, the invisible input of the user is also employed to dig further into the user’s preferred way of using the application. In the identified studies, the invisible input based data collection techniques consist of embedded sensors, subdivided into wearable and internal/smartphone, and external sensors:

**Embedded sensor:** These embedded sensors are usually physically placed in the environment near the object they sense to measure object movement, physiological signals, and environmental variables [24]. The application of embedded sensors appears to be overwhelming external sensors, with 20 (42%) of the articles deploying embedded sensors. Among the embedded sensors, medical sensors and smartphone sensors are two sensors of the most frequent use, accounting for 19% and 17% of the included studies, respectively. Regarding smartphone sensors, some identified studies use the phone camera (6%) (S20, S32 and S36), microphone (4%) (S9 and S20) or accelerometers (14%) (S6, S9, etc.). Various medical sensors (19%) are employed, including heart rate monitors (S3, S5, etc.), pulse oximeters (S42), glucose monitors (S20 and S41), electrodermal activity (S32), electrocardiograms (S11 and S32) and blood pressure monitors (S29). There are also a number of studies (14%) using standalone gait and movement measurement sensors (S39, S43, etc.).

**External sensor:** This type of sensor is used to capture the user’s pose, salient body parts, related objects, etc. Unlike embedded sensors, external sensors are less frequently used with only two types of sensors, the Kinect sensor (12%) (S8, S35, etc.) and the Webcam (2%) (S4), which are mainly used to detect user’s motion.

6.2.3 Coupling data collection techniques. Among these studies that reported their data acquisition techniques (92%), 20 studies (42%) used only one data collection technique. Of these, the majority (70%) employed the data collection technique based on visible inputs. A significant number of studies (38%) used two types of data collection techniques, and 13% used three types of data collection techniques. For studies that employ multiple data collection techniques, 8 articles (16%) collected data through user behaviour data and user input through application. Furthermore, we found that these two data collection techniques were always used together with data collection techniques based on invisible input. This can be explained by the fact that using techniques based on both visible and invisible inputs can identify the needs of the user more accurately and thus improve the quality of adaptation [4]. It is also possible that these articles take into account that the majority of users do not like to spend extra time and effort providing information to the system and that the information provided by users may not always be accurate [5]. Data collection techniques based on invisible input where the user is not directly involved in the information-gathering process can overcome some of the limitations.

6.2.4 Data collection technique and user data. To understand the relationship between different data collection techniques and user data, we computed a bubble chart with bivariate distribution (see Figure 4). Each category of data collection technique can collect several types of user data.
and vice versa. We found that user input through applications is by far the dominant method for collecting data on a wide variety of user data. This is to be expected considering that user input is the primary type of technique used to collect user data (60% of the studies). In addition, user characteristics such as user’s preferences (28% of studies), physical characteristics (14% of studies), and physiological characteristics (12% of studies) are the most popular user data collected through user input, compared to other user data related to tasks or interactions. It is possible that user characteristics data are hard to extract through other data collection techniques.

Figure 4 also shows that the external sensor and techniques based on visible input are mainly used to capture the user’s performance in the game. Another notable trend we observed is that both invisible and visible inputs based data collection techniques can be used to collect most interaction related and user characteristic data. For example, user performance data in a game can be collected by Kinect sensor or user interaction. On the contrary, task specific data can only be collected through techniques based on visible input. It can be explained by the difficulty of task specific data being collected in other ways. To summarise, there is rarely a standard approach that collects data in such a way as to maximise the efficacy of an AUI.

7 RQ3: WHAT ARE THE ADAPTIVE MECHANISMS USED IN GENERATING THE AUI?

In this section, we shift our focus to the adaptive mechanism which covers two key components of the AUI: the adaptive strategy and the adaptation actor. The type of adaptive strategy chosen in an application reveals the key feature aspects that researchers want to extract from a given type of application. Thus, we aim to empirically determine if certain adaptive strategies pair with specific applications. We also examined the role of users during the adaptation process in conjunction with different applications. Specifically, our goal was to create a taxonomy of different adaptive strategies and determine if there is a correlation between adaptive strategies, adaptation actors, and different applications.

7.1 RQ3a: What types of adaptive strategies are used to generate the AUI?

We identified many different types of adaptive strategies used to deliver AUI. We classified these adaptive strategies used in the included primary studies based on [35]. Four adaptive strategies were identified:

- Rule-based adaptation (RuleAD): changes its behavior based on pre-defined rules (S1, S2, S3, S4, S5, S6, S7, S8, S9, S10, S11, S12, S13, S15, S16, S17, S18, S19, S20, S21, S24, S25, S28, S29, S30, S33, S36, S37, S39, S41, S42, S44, S45, S46, S47 and S48).
- Predictive algorithm-based adaptation (AlgoAD): learn complex rules from the users’ data collecting through different sensors, user interaction history (S9, S13, S14, S19, S27, S31, S32, S34, S35, S37, S38, S39, S40 and S46).
- Goal-driven adaptation (GoalAD): changes its behaviour based on defined goals (S18).
- Adaptation through a feedback loop (FeedAD): collect data about the adaptive system’s current state and context. The system may also ask user feedback through questionnaires to further adapt the UI (S2, S11, S13, S19, S34 and S37).

According to our findings, 92% of the articles reported the adaptive strategy they used, of which 36 studies (75%) mentioned that they used RuleAD and 14 studies (29%) used AlgoAD. For example, in S2, the application defines rules for different numbers of correct answers given by the user in the interactive quiz. And in S4, S6, S7, and S8, the activity or performance level thresholds are used to adjust the difficulty level of the exercise or game. A small proportion of studies used GoalAD and FeedAD, representing 2% and 13% of all included studies, respectively. For all the studies that reported adaptive strategies, the majority (71%) used only one strategy to achieve the
necessary adaptation. Among the single-strategy studies, RuleAD (79%) was the most prevalent adaptation method, while the remaining 20% of the studies used adaptive methods based on prediction algorithms. The popularity of RuleAD is not surprising given the complexity of other types of adaptation strategies. In addition to using only one strategy, ten studies (21%) used more than one strategy in their study.

### 7.1.1 Coupling adaptive strategy

For the studies that employ multiple adaptive strategies, the results show that in 6 articles (12%) that used RuleAD, they also used AlgoAD. In 10% of the included studies, RuleAD was accompanied by FeedAD, while in 8% of the cases FeedAD itself was accompanied by AlgoAD. Therefore, it seems that the combination of RuleAD and other adaptive strategy is mostly used in the studies that employ AUI. GoalAD and FeedAD are always used in combination with other strategies, and these two strategies are not often used individually.

### 7.1.2 Adaptive strategies and applications

Figure 6 delineates a bivariate distribution of various types of adaptive strategy according to the application to which they are applied. Examining this data, we found RuleAD which is by far the leading adaptive strategy for various kinds of applications. In addition to the prevalence, we observed trends that FeedAD and AlgoAD have mostly been used in rehabilitation applications, HealPM applications and exercise game applications. This may be because these apps need to adjust the difficulty of the game or rehabilitation exercise to maintain the user’s motivation level (S3, S6, S7 and S14). At the same time, the exercise game should guarantee that reality (the outcome of the workout game) matches the user’s expectations (the perception of their own motor skills). Thus, the application may ask the user for feedback and modify the adaptation accordingly.

![Fig. 6. Bubble chart for adaptive mechanism and types of solution.](image-url)
7.2 RQ3b: Who is adapting the UI?

For RQ3b, we are mainly interested in the role of the user in the adaptation process. We have categorised the adaptation into three categories (manual systems, automatic systems and semi-automatic systems) depending on which system or end-user is responsible for making the adaptation in Section 2.1. Our results analysis showed that nearly half (48%) of the papers employ the automatic system for constructing the AUI (S2, S5, S7, S9, S11, S12, S17, S18, S20, S24, S26, S29, S31, S32, S33, S35, S36, S38, S40, S41, S42, S44 and S45). On the contrary, few studies (15%) reported the use of manual system (S1, S10, S15, S16, S22, S23 and S47). The semi-automatic systems are mentioned in 18 studies, accounting for 38% of all included studies (S3, S4, S6, S8, S13, S14, S19, S21, S25, S27, S28, S30, S34, S37, S39, S43, S46 and S48).

7.2.1 Adaptation actor and applications. We observed certain trends between different adaptation actors used and the corresponding applications, as shown in Figure 6. Most applications made use of semi-automatic system and automatic system, which is expected since the manual system leaves all the burden of adapting to the user [36] and empirical evidence also indicates that users have difficulty in using the adaptable features of manual systems i.e. they do not use them very often. [36, 38]. We also found an uneven distribution of the automatic system studies, where rehabilitation application, persuasive game application, health-promoting, and self-monitoring applications accounted for the largest proportion of automated system studies. In general, these 3 types of applications require a high level of user involvement, and the generated interaction data is used to examine the user’s behaviour or infer the user’s health status. The greater proportion of these three types of applications that use automatic systems can therefore be explained that automated systems yield more beneficial benefits when user involvement in the application is key to achieving the software’s goals.

7.2.2 Adaptation type and adaptive strategy. We also analysed the relationships between adaptive strategy and different adaptation actors in a given application. Applications that adopt adaptive strategies like AlgoAD, GoalAD or FeedAD are frequently seen in automatic or semi-automatic systems. This is because these strategies require complex input from users and regular UI adaptation which is more efficient to be automated instead of operating by the user. For example, changes in the level of difficulty and maintaining the performance of users at an acceptable level are based on data that need to be extracted, processed or calculated constantly, thus more convenient for the system to take responsibility. Moreover, users in many cases lack the knowledge and expertise necessary to modify the interface and may not be aware that changes are either possible or essential [36]. Another correlation we observed was that RuleAD adapts the interface in various ways. There are options for the user to manually change the determent for different variables and then the interface will change accordingly. On the other hand, some solutions change the interface by the system itself dynamically according to specific rules.

8 RQ4: WHAT ARE THE ADAPTIVE ELEMENTS USED IN THE AUI?

The purpose of this RQ is to investigate how adaptive components are currently being utilised and to gain an understanding of how a given adaptive element can be applied to applications targeting different health-related conditions. We refer to the adaptive elements as the type of adaptation, which is categorised as presentation adaptation, content adaptation, and behaviour adaptation (seen Table 8). It is also important to emphasise that the subcategories of the three main adaptive elements we present in this section are the most common of the articles included. Therefore, these subcategories are not necessarily the most appropriate classifications.
Table 8. Classification by adaptive elements

| Type of adaptation | Subcategories | Description (studies) |
|--------------------|---------------|-----------------------|
| Presentation adaptation | Graphic design (29, 60%) | Change the layout, font size, colour, and theme. (S1, S4, S5, S7, S8, S9, S10, S12, S13, S14, S15, S16, S18, S20, S21, S22, S23, S24, S25, S28, S30, S32, S33, S36, S39, S42, S43, S44, S45, S46 and S47) |
|                    | Information architecture (2, 4%) | Change the structural design of information. (S18) |
|                    | Sound effect (1, 2%) | Change the volume of the sound. (S13) |
|                    | Interface Elements rearrangement (2, 4%) | Change the on interface elements by removing, adding, or rearranging. (S13 and S48) |
|                    | Content complexity (5, 10%) | Change the content complexity so that it is easy for individuals to understand and process based on users’ cognitive skills, educational backgrounds, comprehension capabilities and other qualities. (S12, S15, S17, S41 and S47) |
| Content adaptation | Navigation adaptation (2, 4%) | Change the user’s permission to navigate freely or navigation to other modules is suppressed. (S20 and S25) |
|                    | Add on functions (6, 13%) | Add new functions to better assist user use the application, e.g., magnifying function for ageing users (S1, S16, S20, S24, S25 and S30) |
|                    | Different persuasive strategy (4, 8%) | Change pervasive strategies used to motivate the desired behaviour change, according to different user type or status. (S5, S10, S19, S37 and S41) |
|                    | Difficulty level (23, 48%) | Change the difficulty level of the game or exercise based on the motivation state or user performance. (S2, S3, S4, S6, S7, S8, S10, S11, S14, S19, S26, S27, S29, S31, S34, S35, S37, S38, S39, S40, S41, S42 and S43) |
|                    | Multimodal interaction (6, 13%) | Change the modality of the interface based on different contexts of use. (S1, S20, S25, S28, S37 and S43) |

8.1 Types of Adaptation

**Behaviour adaptation.** Our analysis revealed that the most prevalent type of adaptive element is behaviour adaptation which is an adaptation type that changes the type or structure of navigation, activating or deactivating interface elements or interaction modalities of the application [42, 43, 49]. We break behavioural adaptation down as shown in Table 8. We found that difficulty level (48%) is by far the leading adaptive element of behaviour adaptation. This approach has been employed particularly in games, exercise, and rehabilitation applications that seek to continuously engage users by adapting to their physical capacity and health state [4]. The changes in the difficulty level take into account elements such as changing the number or size of puzzle pieces in the game (S7) and target speed during the exercise (S14, S35 and S39). Other common adaptive elements are multimodal interface adaptation (13%) and add-on functions (13%). In S28, for example, the applications changed to voice input when a physician searches for a patient’s medical record number or adds a new order. In S30, the additional module "Magnifying Glass" can be triggered after processing the user’s health information. The remaining infrequent adaptive elements are different persuasion strategies (8%) and navigation adaptation (4%). In S10, the authors changed the pervasive strategies of the healthy eating game for different player types of users. In S20, navigation to other modules of the application was suppressed and emphasis was placed on quick access to emergency services through a highlight feature when a hypoglycemic event happens.

**Presentation adaptation.** Presentation adaptation refers to changing the parameters of the interface elements such as colour, size, the position of objects, font size, etc. [42, 43, 49]. We break presentation adaptation down as shown in Table 8. Graphic design adaptation is performed in 63% of all included studies. This approach can be applied in many ways, for example, by controlling the theme, layout and display. Other possibilities considered in the analysed articles are the change...
of information architecture or sound effects which account for 2% and 2% of all included studies, respectively. Information architecture refers to the variation in the structural design of information. In S18, recommendations for patients with chronic diseases vary in nature, form, and structure, depending on the patient’s condition and his or her medical goals. Adapting the sound effect is mentioned in only one included study (S13), which adjusted the output volume based on the distance between the user and the device.

**Content adaptation.** Content adaptation changes the content level of the interface by adjusting the text, its semantic content, images or explanatory inscriptions [4, 40, 42, 43, 49]. There are only a small number of primary studies that adapt the content level of their interfaces. In our studied papers, the adaptation of content complexity and interface elements rearrangement account for 10% and 4% of all included studies, respectively. Adaptation at the level of content complexity seeks to make content simple to grasp based on users’ cognitive skills, educational backgrounds or comprehension capabilities. The authors of S15 modified the interface of an application to an extremely simplified single-button layout for older people without any IT knowledge. Two studies, S15 and S48, discussed the rearrangement of interface elements, where they put the most frequently accessed items at the top of the corresponding menus.

### 8.2 Combining multiple adaptive elements

We identified that 30 (63%) studies utilised only one type of adaptive element in their interface. 18 studies (38%) adapted more than one type of adaptive element in the interface. For the studies that employ multiple adaptive elements, both performance adaptation and behaviour adaptation are used in 13 studies (27%). Regarding the subcategories, we found that graphic design is by far the leading presentation adaptation subcategories combined with other adaptive elements. On the contrary, other subcategories of presentation adaptation, such as information architecture, sound effects, etc., are not often used in combination with other types of adaptation. Apart from that, subcategories under behaviour adaptation are most often used together. For example, the multimodal interface adaptation is mostly used in combination with navigation, add on functions, different persuasive strategies, and difficulty levels with 4%, 6%, 2% and 4%, respectively.

### 8.3 Adaptive elements and chronic disease

Our analysis indicated that adaptation of presentation and behaviour on the interface are two main types of adaptation mostly used in studies supporting the rehabilitation of stroke, RFCD and ageing (see Figure 7). These health-related conditions are associated with rehabilitation, health monitoring and exercise applications, which appear to always provide adaptation to behaviour level, and graphic design is always used in conjunction with most of the subcategories of behavioural adaptation. For most health-related conditions, few solutions are adapted to the content level.

### 9 RQ5: HOW ARE THE STUDIES EMPLOYING AUI DEVELOPED AND EVALUATED?

In this section, we focus on the approaches used to design and evaluate chronic disease management applications with AUI. The use of scientific and rigorous evaluation methods to evaluate software development methods has long been emphasised by the SE community [15, 57]. In our study, the evaluation of adaptive systems is studied from three aspects: evaluation indicator, evaluation type and evaluation result.

#### 9.1 Design approach

Although the design methodology for AUI is an important part of developing adaptive systems, the literature was disappointingly scant on this matter. According to our findings, only 69% of articles reported the design approach they used to develop adaptable interfaces. Of these, 21% followed
a model-driven approach, and only 3% were based on a user-centred design approach. An iterative design approach and inclusive design approach were used by 2% each. Given that the model-driven approach is overall better suited for devising an AUI [3, 49], the popularity of employing the model-driven approach in developing the AUI is expected. Among the studies using a model-driven approach, we looked for the types of models used to design the AUI, and we identified: the context model (S5); user model (S19, S36 and S42); ontology model (S1); personalisation model (S10); player model (S14); adaptation model (S20); user behaviour model (S14); among others. The context model and user model are the models most cited in different solutions.

9.2 Evaluation approach

We adopted the classification scheme for evaluation approaches from [8]. Figure 8 presents the kinds of approaches used to evaluate the solutions reported in the reviewed papers. It is evident that “Experiment with human subjects” (56%) is the most frequently used means of evaluation. This is followed by "example application" and "discussion" with 15% and 10%, respectively. The "field experiment" was only applied to 8% of the total evaluated papers. The other less common method is "simulation" (4%), "experience" (2%), and "experimenting with software" (4%). For the evaluation method involving human participants, we found that the number of participants between 1 and 10 is applicable for the most significant proportion of all studies, accounting for 16 studies (33%) (see Table 9). The other two large percentages are evenly distributed among the "11 to 20" and "21 to 30" participant groups, accounting for 5 studies (10%). Few studies recruited over 31 participants (8%). In addition, none of the reviewed studies reported on their choice of the number of participants. Although, there has been a great deal of research in the HCI field on the ideal number of participants for various types of studies. [15, 45]. In general, evaluation of systems with AUI typically requires a more rigorous methodology. For further mining, we observed that studies evaluated by human subjects are of a high study quality score, especially for studies testing in the field, at home, or in hospitals (see Figure 8).

9.3 Evaluation Measurements

In terms of evaluation measurements, we excluded studies where the use of evaluation methods is not meant to provide evidence. For example, we excluded studies using "example applications", "discussion" and "experience", since the evidence-based of these evaluation methods are considered quite weak [8]. Therefore, we only considered 31 studies (62%) for this analysis. Through our analysis, we summarised the evaluation indicators into the following six categories by consulting the classification made in [26]: behavioural outcome (BehOut), health/medical status (HeathSta), user
experience (UX), psycho-behavioural determinant (PsyDet), knowledge level (KnowL), and usability metric (UM) (see Table 9). According to [26], these six categories can be summarised into two general categories, mainly **process evaluation** (including UX and UM) and **outcome evaluation** (including BehOut, HeathSta, PsyDet, and KnowL). Following is the breakdown of articles by indicator categories: 22 studies (46%) employ process evaluation while 13 studies (27%) use outcome evaluation. Seven (15%) of the articles undergo both process and outcome evaluation with the goal of using the process evaluation’s early comments to improve the design of the outcome evaluation. To identify the most common evaluation metrics, a thorough review of these methods was conducted as follows. Six studies (13%) of the 22 (46%) studies employed process assessment evaluated based on UM. UX is assessed in all studies using process evaluation. Of the 42% of articles evaluating outcomes, 19% focused on BehOut, 16% studied HeathSta, 6% assessed PsyDet and 6% measured the KnowL of users. Figure 8 further revealed that a high tendency is noted toward the process evaluation (50%) for all kinds of applications.

![Fig. 8. Bubble chart for the type of solution, evaluation approach, evaluation indicator and number of participants](image)

### 9.4 Evaluation Results

Among the included studies, we found that some studies do not provide clear and specific statements about the observed evidence. Many primary studies that were included only discussed the advantages and disadvantages of the solution and did not clearly report the effects of the applied approach. Some studies use real examples and collect evidence of its use informally, only describing how to use a particular method without explaining any specific effects of using the method. In general, the evaluation results showed that in 92% of articles tailoring was **effective**, in 4% **not specify** and in 4% it was **partially effective**.
Table 9. Evaluation details of studies involve human subjects.

| Health relation conditions | Study ID | Evaluation indicator | Length of time evaluation | Evaluation results | General users | Health professionals |
|---------------------------|----------|----------------------|---------------------------|--------------------|--------------|---------------------|
| Stroke                    | S27      | UX                   | 1 session per participant | Effective          | 8 adults     |                     |
|                           | S31      | UX and UM            | 2 week (one session per day) | Effective | 5 adults     |                     |
|                           | S34      | BehOut               | 10 sessions (1 minute each) | Effective | 8 adults     |                     |
|                           | S35      | UX and HealthSta     | 8 session (20 minutes) | Effective | 8 adults     |                     |
| Parkinson                 | S23      | UX                   | 1 session per participant (30 minutes) | Effective | 40 adults    |                     |
|                           | S28      | UX                   | 1 session per participant (1 day) | Effective | 45 doctors   |                     |
| Neurodevelopmental disorders | S8      | UX and UM            | 1 session per participant | Effective         | 9 adults     | 6 therapists        |
| Diabetes                  | S17      | HealthSta, BehOut, PsyDet and KnowL | 1 session per participant | Partially effective | 561 adults   |                     |
|                           | S18      | HealthSta and BehOut | 1 session per participant | NS                 | 15 adults    |                     |
|                           | S3       | UX and HealthSta     | 1 session per participant (10 minutes) | Effective | 28 adults    |                     |
|                           | S9       | BehOut and UX        | 19 days                  | Effective          | 27 adults    |                     |
|                           | S10      | PsyDet               | 1 session per participant (20 minutes) | Effective | 272 adults   |                     |
|                           | S36      | UX and UM            | 1 session per participant | Effective          | 12 children  |                     |
|                           | S42      | UX                   | 1 session per participant | Effective          | 8 adults     |                     |
|                           | S44      | HeathSta and UX      | 3 months                 | Effective          | 28 adults    |                     |
|                           | S45      | BehOut               | 14 weeks                 | Effective          | 19 adults    |                     |
| Cardiovascular disease    | S29      | HealthSta            | 43 sessions (at least 30 minutes each) | Effective | 10 adults    |                     |
| Cancer                    | S6       | UX and UM            | 2 sessions per participant | Effective         | 22 adults    |                     |
|                           | S48      | UX                   | NS                       | Partially effective | 18 adults    |                     |
| Autism                    | S2       | UX                   | 1 session per children participants (30-60 minutes) | Effective | 7 children   | 2 therapists        |
|                           | S22      | BehOut               | 15 weeks                 | Effective          | 9 children   |                     |
|                           | S7       | UX                   | 1 session per participant | Effective          | 10 adults    |                     |
|                           | S25      | HeathSta             | 8 sessions               | Effective          | 25 adults    |                     |
|                           | S46      | UX and UM            | 1 session per participant | Effective          | 8 adults     |                     |
|                           | S5       | UX and UM            | 2 sessions per participant | Effective         | 3 adults     | 4 caregivers        |
|                           | S32      | UX                   | NS                       | Effective          | 10 caregivers|                     |
|                           | S43      | UX                   | NS                       | Effective          | 63 adults    |                     |

* NS: not specified

10 DISCUSSION

The findings of this SLR have been presented in the previous section with respect to the RQs. We summarised all the findings in a mind map, as shown in Figure 9. We will now review these findings and consider potential areas for further investigation.
10.1 AUI for different types of software application

Figure 10 presents a mapping of the identified software types in Section 5 into the aspects of AUI reported in Sections 4, 6, 7, 8 and 9. This mapping is intended to provide the reader with an overview of the types of software associated with different aspects of AUI. We observed that web applications and mobile applications are the primary platforms used to deliver applications with AUI. Figure 10 also indicates that both two channels have a similar trend for targeting users, study sources, user data, adaptive elements and adaptation actors.

- **Targeting user groups**: We found that very few studies adapt for health professionals, and even for applications targeting both the general public and health professionals, these applications are usually not adapted to health professionals (e.g., S2 and S13). The primary responsibility of the health professionals in the included study is to tailor the training or treatment according to users’ health status and other demographic characteristics (e.g., S13 and S15). In future studies, researchers can automate repetitive manual tasks for health
professionals and support for treatment in decision making according to the performance and preference of patients.

- **Varied data collection techniques**: Smartphones have a large number of sensors and other data sources, and more opportunities to collect user information, which can better provide users with information about their health, environment, activities, behaviours and intentions [35]. On the other hand, web applications can leverage a number of external sensors, such as Kinect sensors and webcams. The use of web channels or mobile channels in turn affects the popularity of different types of applications. Mobile applications are predominately utilised as the delivery channel for HealPM applications (See Figure 10), owing to their capacity to capture information that can be used to characterise a person, location or physical entity [1]. We recommend that developers consider the type of data and collection techniques they intend to use when developing different types of software with AUI.

![Figure 10](image)

**Fig. 10.** Bubble chart between the type of solution, source of study, target audience, user data, data collection technique, adaptive elements and adaptation actor

### 10.2 Mapping user data

The goal of utilising user data is to find a balance between the specific data type, the effort from users to input their data/or the system to collect the data, and the associated costs. The AUI would be the most cost-effective when the least number of determinants are found to predict the maximum change in the outcome of interest.

- **Type of data used**: Throughout our study, it is clear that certain types of user data and environmental data are barely touched in the literature (e.g., task-specific data). This suggests that these and other underrepresented data types could be ripe for future applications. In addition, we believe there is an opportunity to combine multiple data types for a more comprehensive representation of the user. According to Section 6.1, user characteristics and interaction data are by far the area with the most effort when it comes to the data source of the adaptation and they are often used in combination with each other. For example, for user characteristics data, some studies used multiple dimensions of user characteristics to achieve the necessary knowledge (e.g., S3, S9 and S17). There is no agreed amount of user information for the AUI, rather it depends on the purpose of the application [29]. Additionally, we are able to correlate different applications with particular data types, primarily because a given data
type is typically preferred for a specific type of application [26]. However, current research has a fundamental problem in the ability to verify and quantify these implicit associations. Thus, there exists an open research problem in explaining which given user data was preferred to be collected as the data source of adaptation for the given application type.

- **Data collection technique**: Based on the analysis in Section 6.2, there is a need for future studies that use adaptive technologies to make the software highly flexible and less expensive by properly combining software and hardware. For instance, in the rehabilitation application, several studies commonly use Kinect sensors for human skeleton tracking (e.g., S35, S37 and S40). However, S4, one of the included studies, track virtual skeleton joints directly from the RGB data captured from a camera, which can contribute to the use of rehabilitation application more accessible and cheaper for a wider population. A medical sensor is a type of sensor that is used frequently, however, this represents additional costs for most people and sometimes leads to their restricted use in hospital environments. Future studies should focus on exploring more lower-cost options for applications which may be suitable for home use.

### 10.3 Decision-making process for adaptation

Detecting the need and making the decision to adapt the interface is the critical procedure of adaptation [2]. According to the analysis of the results in Section 7, there is no one method/strategy that suits all circumstances of adaptation decision-making.

- **Adaptation strategy**: As the results revealed in Section 7.1, most adaptive systems were based on simple decision rules (i.e., if-then rules). Especially for applications which do not require complex adaptation. One downside of utilising basic if-then rules is that the developer must account for any possible variation. The resultant adaptation may be incoherent or sub-optimal for the target user. One previous review study also reported the common usage of sample rules in health applications with tailored information [26]. For future studies, there is an opportunity for leveraging different adaptive strategies to achieve a better balance.

- **Adaptation actor**: We have identified and discussed three different adaptation actors in Section 7.2. The prevalence of automatic and semi-automatic systems is expected since the manual system leaves all burden of adaptation to the users. Regarding the manual system where users perform the adaptation entirely, there is a need for a more natural adaptation to avoid adoption barriers such as time spent learning the tool or delaying the customisation. S5 developed a graphical UI allowing users to specify their own adaptation rules based on contextual elements, triggers and actions, which is difficult for less computer-literate users. Besides that, our review has revealed that a simple rule-based adaptation can distribute the initiative (what initiates the adaptation process) between the user and the system [2]. This means that the user can manually change the variables for different settings or the system itself can carry out the adaptation process according to pre-defined rules. This indicates different levels of user involvement in the adaptation process, which may depend on the willingness of the user to drive the process or the knowledge required for such adaptation. We suggest that there is an important need for research to gain a deep understanding of distributing the initiative between the end-user and the system. This motivates the following questions: What level of automation do users prefer for different types of applications or adaptive elements? How can we control the user’s involvement in the whole adaptation process (e.g., who triggers the adaptation or evaluates the adaptation results)?
10.4 Adaptive elements

Through our analysis conducted in Section 8, it was clear that certain types of adaptive elements are barely mentioned in the literature (e.g., content complexity, interface element arrangement). Graphic design and difficulty level are the most commonly used adaptation among the included studies. As observed in the included studies, the adaptation process usually considers more than one element to be changed in the software. This fact is a characteristic to be highlighted and observed in future studies: what is the combination of adaptation types that users are satisfied with?

Another important issue is that applications designed to promote physical activity and rehabilitation exercises always seem to provide adaptations to behavioural levels and will also incorporate adaptations using graphic design at the same time. Researchers can further analyse which types of adaptations users prefer, especially considering the purpose of the applications. The response to this question may differ according to the user. Thus, examining user types and motives can be an interesting topic for future research in this field. For example, in rehabilitation exercises, does increasing the animate trainer speed and other components related to the difficulty level inspire users more than offering rewards for their achievements?

10.5 System design for the AUI

Based on the results from Section 9, the general lack of information on system design (69% missing) suggests serious deficiencies in the reporting of design methodology in the literature on AUI related to chronic disease management software. As reported in Section 9, descriptions of eHealth interventions are often restricted to focusing on enhanced user experiences and their efficiency in improving health outcomes and behaviours (evaluation results). Few studies in our research explain how the proposed solutions were developed, especially in the early stages of design stages when end users were involved (e.g., S5 and S6). Even with studies that mentioned how they develop the system, very little information was provided without any further description (e.g., S12, S44 and S46). Therefore, we had to abandon them for interpretation and exclude the design approach in the taxonomy (Figure 9). Two previous studies have criticised the lack of information about the design process [10, 26]. Therefore, we strongly recommend more coverage of the system design process for reported studies in future research. Reporting of the design process not only improves the understandability of the proposed solution but also allows readers to better assess the validity and reliability of the reported approaches, tools and applications with AUI.

- **Model-driven approach**: According to Section 9, model-driven approach is the most prevalent approach for developing the software (21%), which is about using modelling languages as programming languages rather than merely as design languages since this can improve the productivity, quality, and longevity outlook [3]. This approach has received the most attention in the adaptive literature [3, 49]. However, none of the studies applies the model-driven approach mentioned the details of the development process.

10.6 System evaluation for AUI

The SE community has long emphasised the use of scientific and rigorous evaluation methods to assess the software [15, 57]. According to the results reported in Section 9, the findings and opportunities for future research are as follows:

- **Length of evaluation time and participants number**: The key finding from Section 9 is that a considerable number of the reviewed studies were evaluated with a small sample and short evaluation period. This concern is of higher relevance in the context of chronic disease [1]. A major reason for this higher relevance is that the effectiveness of chronic disease prevention and rehabilitation applications will require longitudinal studies [40]. In addition,
there is also a greater need for a large number of participants due to the large variations between individuals, which is the basis for adaptive technology [3, 36]. Therefore, we highly recommend that future studies of AUI development for chronic disease applications recruit larger samples of users and have longer evaluation periods.

- **Adaptation evaluation**: Based on evaluation analysis in Section 9, the most common method of evaluation is to simply test the effectiveness (e.g., user experience, behaviour outcome of the users) of the application as a whole, making it difficult to draw conclusions regarding the AUI implemented. The analysis of the evaluation results revealed a lack of consistency in assessing the quality of the adaptation. There are few or no explicit recommendations on how to evaluate the adaptation in order to support the early phase of designing AUI [2]. There are some existing criteria to evaluate the adaptation, such as specification of adaptation ("refers to the user’s ability to specify the actions required to make this adaptation") [30] and user feedback of adaptation ("refers to the ability of the approach to provide feedback about the quality of the adaptation.") [2], but their indicator and usage are not made sufficiently explicit to be adopted by developers for evaluating the adaptation. Thus, there is an opportunity for researchers to develop guidelines and support adaptation evaluation infrastructure for metrics and adaptation comparisons. Such work would allow for clearer and more concise evaluations of adaptation, solidifying claims made from the results of a given evaluation.

11 **THREATS TO VALIDITY**

Even though this systematic review was carried out following a well-established technique [27], our review still has some limitations, most of which are related to our search methodology and the data extraction process. In this section, we will discuss potential threats to the validity of our empirical investigation.

11.1 **Construct validity**

The extent to which the research reflects the researcher’s intention and what is investigated by the RQs [56]. The inadequacy of the search and study selection process is the most evident bias that might compromise the construct validity of this study [46]. For example, although the concept of the AUI is well known, systems that employ it may also be referred to by terms like "smart user interface" or "intelligent user interface". To mitigate any possible threat in the search strategy, we employed two strategies: 1) we concluded that missing such terms posed a negligible risk in this SLR after doing several rounds of trial searches in six well-known digital libraries. 2) we consulted the search strings utilised in previous SLRs [4, 16] and used the PICOC criteria to ensure that the search was thorough and comprehensive. As a result, our search approach works well enough to identify significant papers in the related field. Another threat to construct validity lies in the search of paper metadata (i.e., titles, abstracts, and keywords) in most databases. It is likely that some publications with no validated reference in their metadata were systematically rejected.

11.2 **Internal validity**

The extent to which the design and execution of our SLR study are likely to avoid systemic errors [56]. The derived taxonomy characterises the field of AUI designed for chronic illness, as the key contribution of this study. To mitigate any errors in the proposed taxonomy, we took three strategies: 1) We developed a data extraction form to gather and analyse data consistently in order to answer the SLR’s RQ. 2) Four authors extract the same number of the included papers independently and compared the extracted data to check if there was any contradicting information. 3) We followed the open coding process of constructivist grounded theory [7]. In our SLR, each attribute classification was reviewed and refined by at least three authors until all three agreed.
boost the integrity of our taxonomy and increase the transparency of the data extraction process, all data extraction details are included in the supplementary material so that the reader can confirm the reliability of the information extracted.

11.3 External validity
The extent to which the original studies are representative of the reviewed field may result from selection bias [56]. To mitigate this bias, we implemented the following three steps: 1) We strictly executed this SLR according to the SLR protocol. The SLR protocol was arranged by one author and subsequently refined by other authors. The initial study set was refined using inclusion and exclusion criteria such that only studies that meet the scope were included. 2) Any disagreements that surfaced during the study selection process were resolved during the internal discussion. After the conversation, we also documented the reasons for inclusion or exclusion. 3) We also used snowballing techniques to find as many relevant papers as possible to reduce selection bias.

11.4 Conclusion Validity
Potential biases regarding the existence or absence of relationships may lead to incorrect conclusions [56]. To mitigate this threat, the data extraction results were plotted and correlated using various graphs in addition to textual descriptions. This helps to enhance the traceability between the extracted data and the conclusions.

12 CONCLUSION
We presented a SLR of the primary studies related to AUI as used for chronic disease related software applications. Our work used the guidelines laid out by Keele [27] for performing SLRs in SE. We generated a taxonomy that pertains to different aspects of applying AUI to chronic disease related applications. Our analysis of 48 included primary studies allows concluding that the most used source of data for the adaptation, data collection techniques, the decision-making process of the adaptation and the final action made to the interface. The concepts described in this review should aid researchers and developers in understanding where AUI can be applied and the necessary considerations for employing AUI in different chronic disease related applications. Key future research directions include (1) investigating the role of health professionals in the adaptation process and how to benefit health professionals by boosting their efficiency in their everyday job, (2) exploring user’s preference for the given data to be collects as the basis of the adaptation, (3) exploring innovative, lower-cost and effective options of data collection techniques, (4) exploring combinations of different adaptive strategies and level of automation users prefer for given types of the application or adaptive elements, (5) exploring adaptive elements users prefer, considering the purpose of the different applications, (6) following available standard reporting guideline for the development of original researches, and developing effective guidelines of evaluating the merits of adaptation approaches in the context of chronic disease applications.

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Adaptive user interfaces in systems targeting chronic disease: a systematic literature review

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