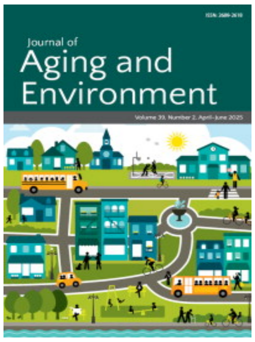

Journal of Aging and Environment

ISSN: 2689-2618 (Print) 2689-2626 (Online) Journal homepage: www.tandfonline.com/journals/wjhe21

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To cite this article: Divya Saleela, Adekunle S. Oyegoke, Jamiu A. Dauda & Saheed O. Ajayi (22 Jul 2025): Development of AI-Driven Decision Support System for Personalized Housing Adaptations and Assistive Technology, Journal of Aging and Environment, DOI: 10.1080/26892618.2025.2534956

To link to this article: https://doi.org/10.1080/26892618.2025.2534956

JOURNAL OF AGING AND ENVIRONMENT
https://doi.org/10.1080/26892618.2025.2534956

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Development of AI-Driven Decision Support System for Personalized Housing Adaptations and Assistive Technology

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ABSTRACT

Artificial Intelligence is transforming the healthcare sector, providing innovative solutions to empower individuals and make medical support more personalized. This study introduces a novel AI-driven platform that links diseases and symptoms to relevant assistive technologies and housing adaptations, ultimately developing a tailored knowledge base for individuals diagnosed with complex chronic conditions such as muscular dystrophy. The platform development entails the integration of advanced Natural Language Processing (NLP) techniques and fuzzy matching algorithms into a user-friendly web-based interface. This enables successful interpretation of user input queries and generation of real-time tailored actionable insights and personalized recommendations for housing adaptation and assistive technologies. This research showcases a scalable, innovative method of patient care that revolutionizes the existing landscape by integrating new AI methodologies into healthcare databases to generate impactful and empathetic elderly and disabled care. The proposed system obtained a query resolution accuracy of 98% and aims to bridge critical gaps in healthcare and housing accessibility by offering solutions and a sense of empowerment to those navigating the challenges of chronic and progressive conditions.

KEYWORDS

Artificial Intelligence in healthcare; decision support systems; assistive technologies; housing adaptations; natural language processing; healthcare accessibility; fuzzy matching

Introduction

The home environment plays a crucial role in shaping well-being, independence, and quality of life, particularly for individuals experiencing impairments (World Health Organization [WHO], 2011). It is not just the physical structure, a home provides individuals with a sense of belonging, freedom, and independence (Sixsmith, 1986). For the elderly and people with disabilities, being in a controlled environment of a home instead of an institution

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fosters dignity, promotes autonomy, and reinforces identity (Imrie, 2004). Naylor et al. (2016) reported that living at home provides a person with a sense of worth and belonging that is often compromised in institutional care.

It is paramount for a person with a disability to live at home because it allows customized support tailored to his or her unique needs. The requirement of these patients cannot usually be met by institutional care, while in the home, there are modifications that can be made such as installing ramps, customizing furniture, and using technological devices that are designed to fit individual requirements (Ma et al., 2022). These changes enhance the persons' self-reliance, and improve their quality of life, as well as the relationships with family, neighbors, and the environment. According to Age UK (2024), modifications in the home enhance the individual's ability to navigate and participate in the surrounding environment, whereas institutional care might restrict this.

The Disabled Facilities Grant (DFG), a UK government-funded initiative, provides crucial support for individuals needing adaptations to make their homes more accessible and habitable (GOV.UK, n.d.). The UK Government has committed to funding £711 million to the DFG in the financial year 2025–2026, which will help local authorities to provide home modifications such as ramps, stairlifts, and accessible bathrooms, reducing barriers for individuals with mobility challenges (Housing LIN, 2025). However, despite these adaptations' clear benefits, inefficiencies in the implementation process can cause significant delays. Many individuals who rely on these essential changes face frustratingly long waiting periods, highlighting challenges within the system rather than the builders' fault alone (Oyegoke et al., 2024). Age UK reports that statutory limits for waiting are frequently exceeded and sometimes last over 18 months. These delays make people live in homes that are unsafe, inadequate, and putting their lives at risk (Tucker, 2024). An aging population and a rising prevalence of disabilities further burden the existing system, which is evidenced by Sherzad (2024), who notes that a woman with mobility issues is stuck without a proper bathroom, struggles to move around her home, and cannot leave out because of the delay in the promised adaptation. To enable timely and effective home adaptations that promote safety and independence, these challenges will need to be addressed using scalable solutions.

Although, the contribution of the Occupational therapist (OT) is appreciable in the in-house adaptations for people living with disabilities, as the OT examines the physical, environmental, and psychological barriers the individual can experience and suggests modifications to enhance their accessibility and improve safety (Tucker, 2024). However, (Matus et al., 2020) state that their assessment efficiency is affected by the current obsolete manual processes and OT shortages (Royal College of Occupational Therapists, 2019).

Meanwhile, (Tang et al., 2024) suggested that transformative technologies such as AI and ML algorithms will enable an accelerated disease detection, tailored intervention, and effective home adaptations to meet the needs of humans. For instance, (Divya et al., 2022), integrated Generative Adversarial Networks (GANs) and optimization algorithms to analyze MRI scans and detect brain tumors. This shows how AI can speed up diagnoses and provide more precise results, ultimately improving care and offering hope for better patient outcomes. Similarly, in housing adaptation, (Logothetis et al., 2023) highlighted that AI systems can analyze comprehensive data about an individual, such as health profiles, mobility needs, and environmental factors, to develop personalized recommendations on how they could adapt to their home. These systems prioritize these adaptations by the speed and context of their response and encourage each solution to be readily available, safe, and cost-effective.

In addition, AI has the potential to increase the efficiency of OTs by automating recurrent tasks and allowing them to focus on timely interventions. Given the limited number of OTs, which is a considerable cause of delays (Zhou et al., 2019). AI can help reduce the burden and ensure that procedures are carried out more efficiently. The integration of AI in housing adaptations not only accommodates personalized needs but also produces systemic benefits by possibly alleviating issues such as resource constraints and administrative inefficiencies. For instance, AI can recommend voice-activated devices for mobility challenges or adaptive lighting for visual impairments. While humans can carry out these tasks, AI enhances efficiency, ensures continuous monitoring, and provides tailored data-driven insights, making housing adaptations more proactive, scalable, and accessible. AI-enabled systems minimize decision-making constraints and allow therapists to provide solutions to universal design (Kaelin et al., 2024). Varnosfaderani and Forouzanfar (2024) validated the trend, explaining how AI-led suggestions fulfilled the requirements of people who suffer from age-induced or temporary healthcare issues. Despite AI's potential to bring reliability, efficiency, and speed to home adaptations by eliminating extended delays, its full integration for personalized housing adaptations has not yet happened. This is due to high costs, lack of standardization, and insufficient research on user-specific needs (Rashid & Kausik, 2024).

This research establishes that there is a dearth of personalized AI-driven solutions in housing adaptations. As such, this study presents the development of an AI-Driven Decision Support System for personalized housing adaptations and assistive technology (HOME-AI). This study presents a system development, which consists of three modules that focus on housing adaptation needs assessment, design customization, and smart assistive technology. The housing adaptation needs assessment evaluates comprehensive health profiles, followed by the design customization module provides user-centric housing accessibility recommendations, and a smart assistive technology module identifies and matches the user input to the individual user requirements. The project integrates Large Language Model (LLM) with fuzzy matching and NLP techniques to provide conversational, empathetic, and actionable responses. This integration ensures that users receive tailored recommendations, enhancing safety, mobility, and independence while making the adaptation process more efficient and responsive to individual needs. Following the WHO's framework ICF (World Health Organization [WHO], 2001), the HOME-AI system considers medical and environmental needs to ensure its multidimensionality.

The rest of this paper is organized as follows: The next section provides a brief background on housing adaptations, assistive technologies, and AI applications for personalized support systems, while the following section presents the design and development of Home-AI. The subsequent section discusses the experimental results and the system evaluation, while the final section contains the conclusion and future work.

Related works on housing adaptation and assistive technologies

In recent years, there has been a considerable increase in research focused on the examination of housing adaptations, an analysis of assistive technologies for inclusive living, and an evaluation of AI-driven smart building technologies in personalized support systems. In response, several studies have systematically reviewed the existing literature, and analyzed trends, challenges, and advancements in the field to provide a comprehensive understanding of current developments. Figure 1 illustrates the distinct areas of research focus used as the background study for the development of the Home-AI system.

At the outset, several studies have systematically reviewed the impact of home modifications on independent living. For instance, Iwarsson (2015) focused on the significance of monitoring and adjusting residential environments to match the physical and cognitive needs, highlighting practical adjustments including ramps, grab bars, and wider doorways. Iwarsson's findings emphasized the need to incorporate accessibility features into the housing design to increase safety and independence. Similarly, Carnemolla and Bridge (2019) investigated the role of home modifications in reducing care needs for aged individuals and people with disabilities. These findings (Carnemolla & Bridge, 2020; Petersson et al., 2008; Wahl et al., 2009) suggested that well-structured adaptations could significantly decrease the dependence on external caregivers, thereby improving overall well-being and reducing long-term healthcare costs.

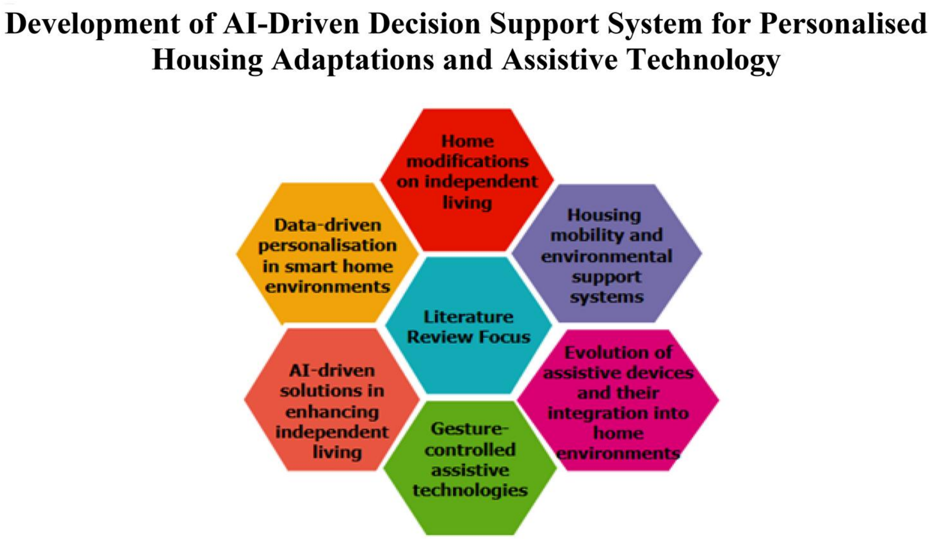

Figure 1. Key focus areas in literature review on independent living.

In addition to studies focusing on individual-level housing modifications, research has also addressed the broader context of housing mobility and environmental support systems. Causa and Pichelmann (2020) analyzed housing mobility patterns across OECD countries. Their study suggested that while home adaptations enable aging in place, residential mobility remains a critical factor in determining access to supportive living environments. This study aligns with the results from Newton et al. (2023) summarizing the role of housing adaptations in supporting people with dementia, highlighting how certain adaptations can assist in everyday tasks and reduce cognitive strain. These studies (Davern et al., 2020; Pollack et al., 2023) collectively indicate that well-designed housing adaptations provide greater individual autonomy and, therefore, contribute to more sustainable healthcare and social service frameworks.

Likewise, multiple studies have examined the evolution of assistive devices and their integration into home environments. For example, Buoncompagni et al. (2017) conducted a review on emerging assistive technologies, identifying challenges in system design, user acceptance, and performance assessment. This study highlighted the need for the seamless integration of assistive technologies with existing home infrastructures to ensure effective support for individuals with disabilities. Furthermore, Vigouroux et al. (2023) explored speech-based interfaces designed for inclusive home adaptation. According to their findings, voice-controlled devices (Crosby et al., 2023; Khosravi & Ghapanchi, 2016; Mun & Kim, 2024) could significantly enhance accessibility by offering simple, hands-free control over domestic tasks, especially for people with mobility disabilities.

Although previous studies primarily focused on voice-based solutions, recent research has expanded toward gesture-controlled assistive technologies. Fatima et al. (2024) proposed a smart home automation system using IoT in combination with Machine Learning (ML) and a gesture recognizer for patients facing auditory challenges. The results of their study confirmed that gesture-based controls are a suitable alternative for users who have difficulty with voice or touch-based interfaces. Overall, these studies (Kheratkar et al., 2020; Yang et al., 2025) illustrate that the integration of innovative assistive technologies can transform home environments into more accessible and inclusive spaces, fostering independence and improving quality of life.

Similarly, several studies have reviewed the role of AI-driven solutions in enhancing independent living for individuals with cognitive decline. For example, Alimoradi and Gao (2021) systematically reviewed smart building technologies designed for cognitively declined occupants, focusing on IoT and AI-based solutions. This study highlighted the potential of these technologies, including fall detection, activity recognition, and behavioral monitoring, to enhance safety and autonomy. These findings (Ajaykumar & Huang, 2023; Cao et al., 2024; Sun & De Florio, 2021) suggested that AI-driven home automation could significantly reduce reliance on caregivers by enabling real-time environmental adjustments tailored to individual needs.

In addition to studies that solely investigate AI-based monitoring and support, broader research has explored the role of data-driven personalization in smart home environments. Recent developments focus on the usage of predictive modeling, behavioral analysis, and adaptive ML (Marufuzzaman et al., 2021; Reyes-Campos et al., 2021; Saleem et al., 2023) making it more convenient to adapt the home, based on user preferences and routines. This aligns with the broader movement within AI-driven assistive living, where intelligent systems are increasingly relied upon to improve accessibility and overall user experience. With ongoing research in this domain, the future of AI and smart building technologies can potentially transform home automation, creating personalized support systems that provide highly tailored solutions for those living with physical and cognitive disabilities.

The existing body of research explored various advancements and shortcomings in healthcare and housing accessibility, along with solutions to enhance the autonomy of individuals. Their findings highlight significant potential for advancements in these areas, particularly the role of AI and IoT in transforming accessibility. However, challenges such as scalability, lack of personalization, and limited real-world applicability remain. To address these challenges, this study presents a novel system, HOME-AI that utilizes AI-driven conversational models, keyword mapping, and dynamic recommendation algorithms to provide tailored housing adaptations and assistive technology solutions, that enhance the autonomy of individuals. By prioritizing inclusivity and adaptability, this system will make housing adaptation process more efficient and responsive to individual needs.

Methods

The development of HOME-AI system involves the integration of disease diagnosis, recommendation for assistive technology, and home adaptation which represent a significant intersection of healthcare and AI. The objective of healthcare professionals, AI developers, and assistive technology providers, is to bridge the gap between those who receive healthcare services and those who have no access to them, such as individuals in remote areas, underserved communities, or those with mobility limitations. Figure 2 illustrates the comprehensive development framework of the AI-driven Home-AI system. It begins with interactive input query processing, where queries

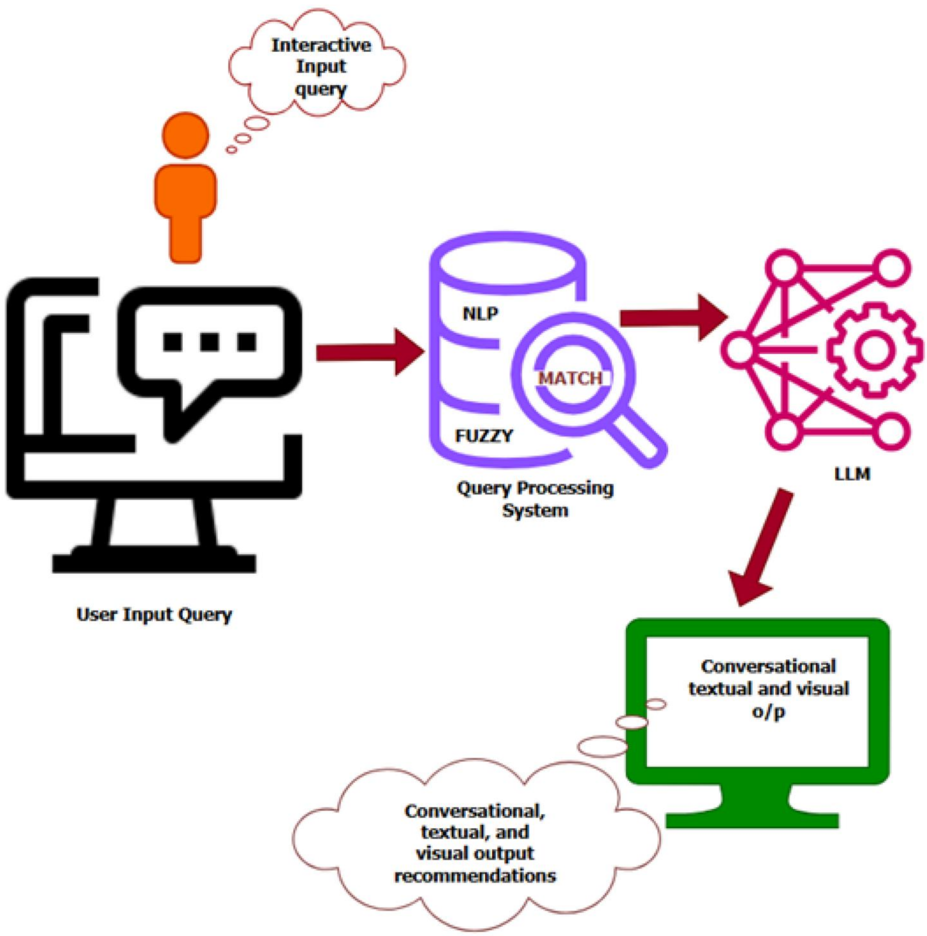

Figure 2. Architectural framework of the home-AI DSS.

undergo NLP and Fuzzy Matching techniques to extract the relevant disease or symptoms keyword. The extracted keyword is then analyzed to generate personalized healthcare and housing adaptation recommendations using LLM. The LLM ensures conversational output responses, incorporating text-based insights, relevant visual data, and external references such as the NHS Official Page for additional trusted information. This structured approach enhances decision-making by providing comprehensive, user-friendly, and visually enriched tailored recommendations.

Figure 3 illustrates the query processing framework of Home-AI, leveraging LLM with NLP and curated data sets from trusted repositories such as NHS (NHS Inform, n.d.) and Mayo Clinic (Mayo Clinic, 2019) to provide user-specific actionable responses. The user inputs in terms of conversational queries are passed through a multi-tier deployment of exact, synonym, and fuzzy matching techniques to extract the relevant keywords from the descriptive user inputs. This approach is adopted to accommodate

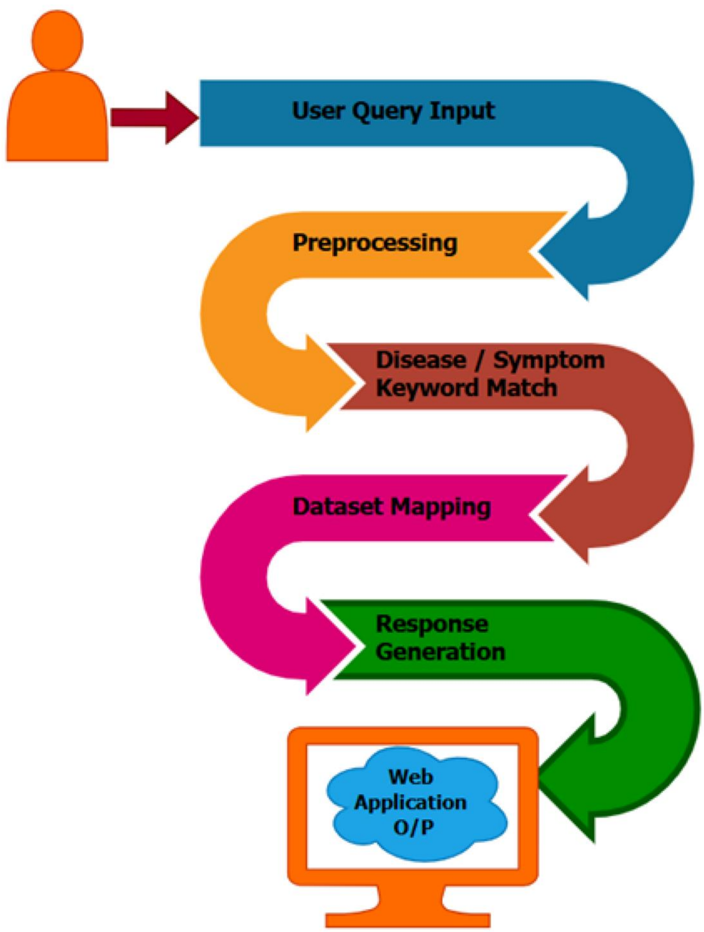

Figure 3. End- to-end user query processing framework.

variations in the input phrasing, which are common in user queries, thereby improving accuracy and user satisfaction as highlighted by Cheng et al. (2010). After the query resolution phase, personalized recommendations for assistive devices and home adaptability are offered based on existing clinical guidelines and best practices. In addition, a transformer-based LLM generates contextual, empathetic responses to facilitate user engagement. A dynamic and responsive web interface is integrated to enable seamless real-time interactions and scalability for diverse user needs.

Data sources and pre-processing

This research is grounded on processing datasets from publicly accessible databases like NHS and Mayo Clinic. This study utilizes three real-time datasets, each containing over 500 entries. The initial dataset (dataset-1) is designed to draw connections between specific disease and their respective symptoms. The second (dataset-2) and third datasets (dataset-3) links symptoms with corresponding assistive technologies and home adaptations, permitting specific recommendations to optimize accessibility and safety. These datasets are crucial because the former is used to understand and analyze symptoms related to diseases for accurate diagnosis and targeted treatment, while the latter links symptoms to assistive technologies and home adaptations with tailored recommendations.

The pre-processing phase is initiated among these datasets to ensure the readability of the input and to obtain optimal accuracy for the Home-AI system. In this phase, the system normalizes the input which minimizes errors with matching, enhances synonym mapping, and it provides robust keyword extraction. This preprocessing improves the overall accuracy and robustness of the system. To unify the naming conventions across heterogeneous data points, all the headers will be standardized to make the subsequent querying of the data easier. Keyword synonyms will be retrieved by WordNet, a lexical database widely used in the field of NLP (Miller, 1995). A keyword-synonym map of synonyms is built for the real-time contextual matching of user queries with dataset entries. This preprocessing pipeline can tolerate noise in the data while preserving its semantic value, allowing for robust and accurate handling of queries.

Once pre-processed, the query undergoes a three-phase matching process. The first tier performs a simple exact match of normalized input with keywords in the dataset-1. The second-tier initiates matching based on synonyms when the precise correspondence is not found in the previous tier. In this manner, the precomputed keyword-synonym map, using WordNet from Natural Language Toolkit (NLTK), is used to find keywords that are contextually similar to the input so that the system can account for divergencies in phrasing from user query (Navigli, 2009). Recent advancements in NLP have demonstrated that pre-computed synonym mappings can enhance the efficiency of tasks by grouping semantically similar words and thereby enabling real-time contextual matching of user queries with dataset entries (Xu & Lu, 2016). The final tier is based on fuzzy string matching that computes token similarity scores as a function of token sort and set ratios, which is considered valid for a score of 80% or above (Manning et al., 2008). Henceforth, the multi-tiered pre-processing pipeline is designed to handle non-exact or weakly word searches in the input, while retaining its semantic integrity, robustness and accuracy in query handling.

Recommendation generation

Following successful query resolution, the system generates personalized recommendations based on the identified symptoms or diseases. Recommendations are drawn from mappings in the datasets, which link the extracted disease or symptom keyword from dataset-1 to assistive technologies and home adaptations from dataset-2 and dataset-3 respectively. The assistive technologies are informed by principles of rehabilitation engineering and evidence from clinical guidelines provided by NHS and Mayo Clinic. For instance, a person with a motor impairment might be recommended an ergonomic tool or an adaptive device for their needs, while someone with mobility impairments might look for assistive technologies such as wheelchairs or rollators.

Housing adaptation recommendations are personalized based on best practices in occupational and physical therapy, guided by the WHO's ICF (WHO, 2001), the ISO 9999:2016 standard for assistive products (International Organization for Standardization, 2016), and practical guidelines from the Muscular Dystrophy UK Adaptations Manual (Muscular Dystrophy UK, n.d.) to enhance safety, accessibility, and quality of life. For instance, revamping of domestic space for wheelchair accessibility, widening doorways, and installing grab bars are housing adaptation recommendations for neuromuscular disorders. These interactive housing recommendations are designed with descriptive templates to ensure that users have clear and actionable insights, providing them with easily understandable suggestions for housing adaptations like above so that they can implement them effectively.

Conversational response enhancement

The pre-trained LLM, Google FLAN-T5-small (Chung et al., 2022), from Hugging Face Transformers, is integrated into the system to promote an intuitive and empathetic user experience. This integration is achieved by initializing this model as a text2text-generation pipeline, followed by defining a cache directory for efficiency, embedding it within FastAPI endpoints for real-time inference, and implementing fallback mechanisms to handle errors and prevent redundant conversational responses. Google FLAN-T5-small is a transformer-based architecture, which has already proven great success in tasks of natural language generation, giving contextually appropriate answers. For each user query, the model generates a coherent and conversational response that synthesizes the information regarding the identified diseases, symptoms, and recommendations. The language model not only allows users to receive relevant updates but also makes them feel supported in their interactions.

To ensure robustness, the system includes a fallback mechanism. In those cases where the language model is not able to come up with an appropriate output due to errors, repetition, or irrelevance, pre-defined templates are used to ensure that a meaningful and contextually relevant response is always provided. These templates are designed to work seamlessly with the model-generated responses. This dual strategy leverages the advantages of both ML and rule-based methods, ensuring a seamless and consistent user experience.

Web application development

An interactive Graphical User Interface (GUI) is developed with FastAPI, a modern web framework known for its speed and asynchronous capabilities (FastAPI, n.d.) so that users can simply input queries about diseases or symptoms and receive conversational outputs. These conversational empathetic outputs include examples of the person's symptoms, assistive technologies, and home modifications. Moreover, the interface includes more personalized tools for navigation related activities, participation limitations, and housing factors for particular use cases like muscular dystrophy.

The interface is designed using custom Cascading Style Sheets (CSS) to enhance responsiveness, accessibility and support real-time interactions through asynchronous JavaScript. The application architecture is built on the client-server model, where the frontend is responsible for user interactions and the backend processes queries and fetches the relevant data. This modularity ensures a seamless experience for end users on all devices whilst keeping the architecture scalable and maintainable.

Deployment and scalability

The application is hosted locally and publicly accessible through Hugging Face Spaces, while Ngrok is used as a secure tunneling service (Inconshreveable, 2015) for development and testing, enabling users to access the DSS in a controlled environment and provide real-time feedback. Scalability is built into the system architecture with efficient data retrieval mechanisms and asynchronous processing, to accommodate a wide range of user queries. The system is scalable as it employs a modular architecture along with pre-defined LLM templates, supports asynchronous processing in FastAPI, and can be deployed on cloud platforms with auto-scaling. The prolongable datasets and functionalities can be integrated without compromising performance making it adaptable to enormous healthcare applications.

Results and discussion

The proposed system embodies a significant development in the direction of addressing health-related queries, as it interprets user inputs dynamically and recommends corresponding assistive technologies and home adaptations to aid users in their quest to secure better health outcomes. The system bridges the gap between clinical knowledge and actionable, user-friendly outcomes flawlessly. This adaptable AI-driven DSS is sensible and ensures that it can process different, flexible, and interactive queries and fulfill real-world healthcare challenges.

The system is evaluated against three component aspects: user query accuracy resolution, user interaction quality, and user interface design effectiveness. It can administer a diverse set of conversational user queries seeking medical assistance, reflecting natural language patterns. These queries are usually expressed as a question or descriptive sentence and are processed to extract relevant keywords and provide contextual recommendations. The system's capacity to understand and respond to natural and conversational queries ensures intuitive interaction and personalized recommendations based on user needs. This feature demonstrates the versatility of the system to address a wide range of healthcare-related inquiries in a human-centered design.

Figure 4 depicts the query resolution architecture of the proposed system, which links the user inputs to the symptoms and systemically categorizes the recommendations associated with the most relevant assistive technologies and home adaptations. Also, it provides a cohesive user experience that interprets the recommendations quickly and intuitively. Apart from the web interface, the system's mapping process is critical for connecting healthcare issues to actionable recommendation outcomes.

Figure 5 illustrates a systematic mapping of Asthma disease and its symptoms to specific assistive technology and home adaptations based on a descriptive user input query: "I have Asthma," whereas Figure 6 illustrates the corresponding user-friendly web interface of the query. This ensures that each request is appropriately handled and transformed into an action

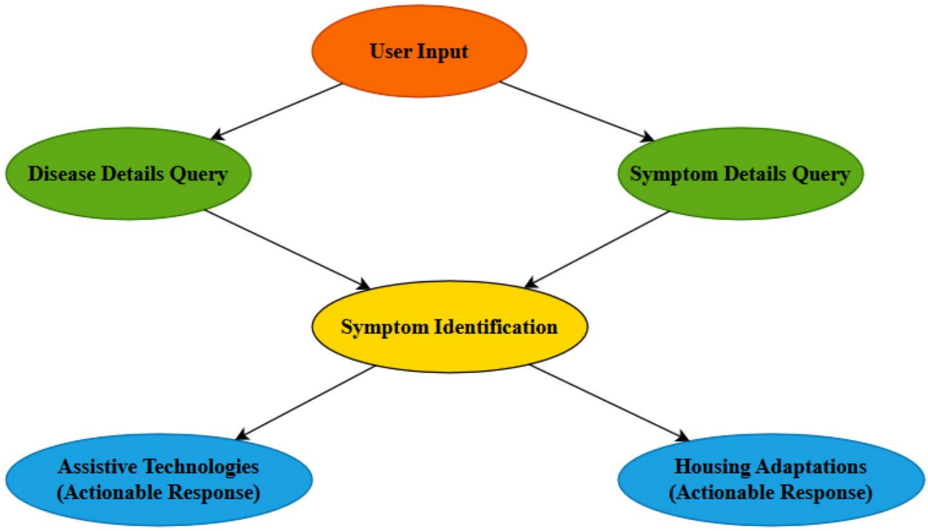

Figure 4. Query resolution architecture: User Input → Symptoms→Assistive Technologies and Home Adaptations.

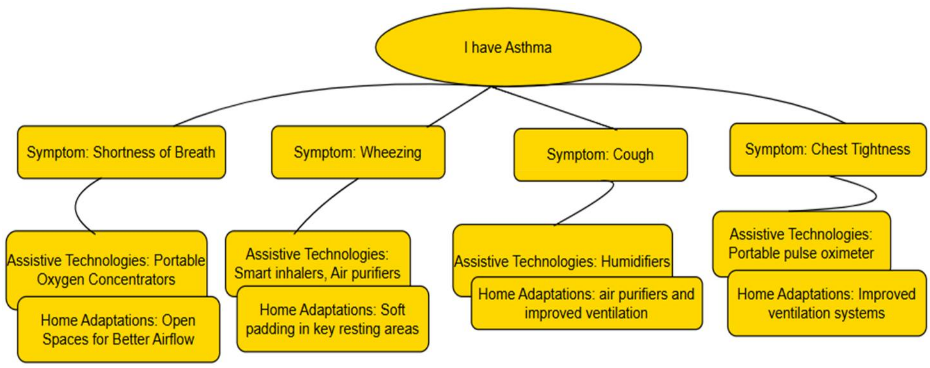

Figure 5. Query resolution of user input "I have asthma."

solution. By placing the patient at the center of the process, the proposed system is more user-oriented and accessible than the existing technology and is thus better suited and effective at fulfilling healthcare expectations. Its performance underscores the significance of translating medical expertise into practical applications, paving the path for future innovations that prioritize user-centric healthcare solutions.

In this study, the efficiency of query resolution is evaluated using an innovative metric called Query Match Accuracy (QMA), which assesses the precision and relevance of query-to-dataset matching such as a disease or symptom and predefined entries in the database. It is calculated as the ratio of the total weighted contributions of match types such as Exact Match (E_{Match}), Synonym Match (S_{Match}), and Fuzzy Match (F_{Match}) to the total weights, ensuring a normalized score (see Equation 1). The E_{Match} score is

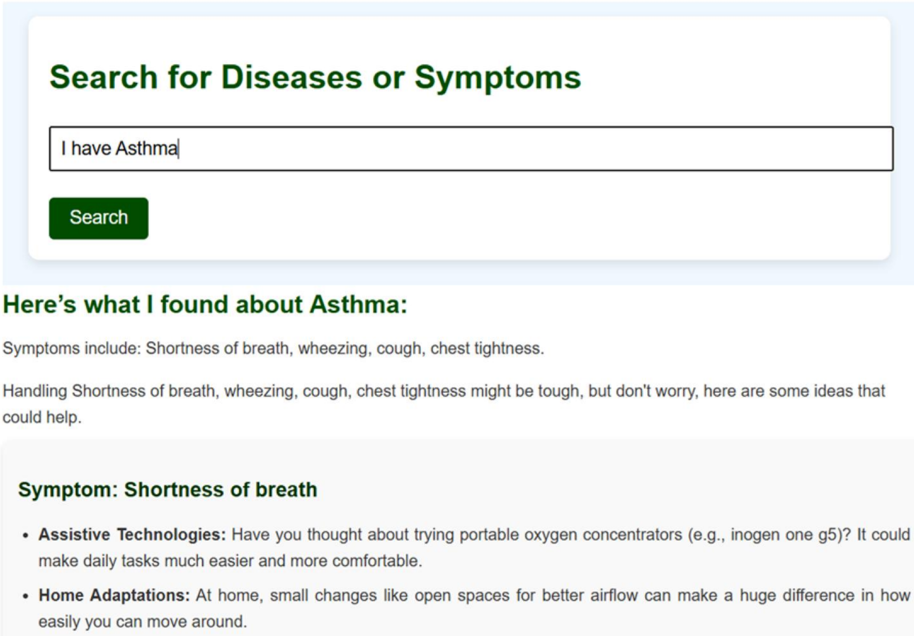

Figure 6. GUI results of the query "I have asthma."

assigned a value of 1 if the input exactly matches an entry in the dataset-1, and 0 otherwise, whereas S_{Match} checks for any synonyms of the input in the dataset-1 and assigns a score of 1 when a synonym is found. Finally, the F_{Match} score is determined using approximate string-matching techniques, such as Levenshtein distance, to assess how closely the input resembles predefined terms, with a score ranging from 0 to 1. The final score is particularly valuable in providing more accurate results in applications where precise matching may not always be possible, such as when dealing with misspelled, abbreviated, or contextually varied input queries. A higher final score indicates a better overall match, while a lower score reflects a weaker correlation between the input and the dataset. For example, an E_{Match} has a higher accuracy and weight due to its definitive correspondence, while S_{Match} and F_{Match} contribute proportionally less. The denominator, the sum of weights, normalizes the result, maintaining interpretability even with varying match types. This makes QMA particularly valuable for quantifying the quality of matching algorithms, such as in healthcare datasets where accurate identification of diseases or symptoms from complex queries is critical.

$$QMA = \frac{Wi * E\_Match + Wj * S\_Match + Wk * F\_Match}{Wi + Wj + Wk} \tag{1}$$

where,

$$E\ \text{Match} = \begin{cases} 1, & match \\ 0, & non - match \end{cases}$$

$$S\ \text{Match} = \begin{cases} 1, & match \\ 0, & non - match \end{cases}$$

$$F\ \text{Match} = \begin{cases} normalized\ between\ 0\ and\ 1 \end{cases}$$

and W_i, W_j, and W_k represent weights of E_{Match}, S_{Match}, and F_{Match} respectively with their sum is always 1.

Table 1 shows the accuracy of the query resolution process quantified using the QMA metric, which measures the ratio of correctly resolved queries to the total number of queries tested. For a dataset of 100 queries, the system achieved a QMA of 98%, demonstrating high reliability. The performance for different query types, including direct matches, synonym-based matches, and fuzzy matches, is presented in Table 1.

The user interface of the DSS is also examined by verifying the way that the information is designed and organized while ensuring that the information it provides is both structured and intuitive. The output is organized in a structured way so that symptoms are categorized into distinct components, along with recommendations that pertain to each symptom. This systematic presentation enabled users to easily comprehend and implement the recommendations provided.

Figure 7 illustrates the mapping process of the system depicting its capability to accurately map symptoms and progressively align them with assistive technologies and home adaptations. For instance, a symptom such as "Blurred Vision" might be linked to "magnification software" as a potential assistive technology, while "sleep disturbances" could lead to recommendations like "smart sleep therapy devices" or "blackout curtains" for home adaptations. This systematic approach can be considered as transforming the process from symptom identification to practical recommendations, reducing uncertainty and enhancing the user's confidence in the results.

The system's usability is further demonstrated through its ability to generate outputs tailored to specific queries. Figure 8 illustrates the results of

Table 1. QMA evaluation.

Query type	Number of queries	Correct matches	QMA (%)
Exact match	40	39	98
Synonym match	35	32	91
Fuzzy match	25	22	88

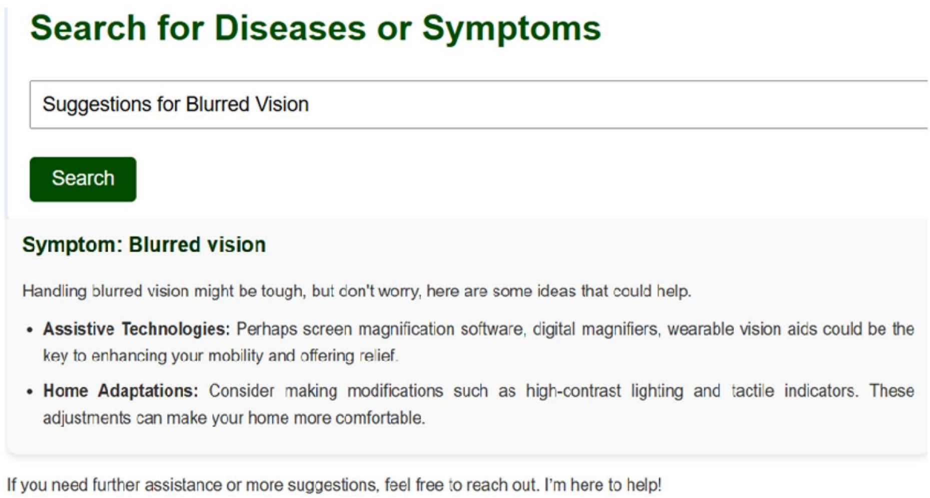

Figure 7. GUI results of the symptom query "Suggestions for blurred vision."

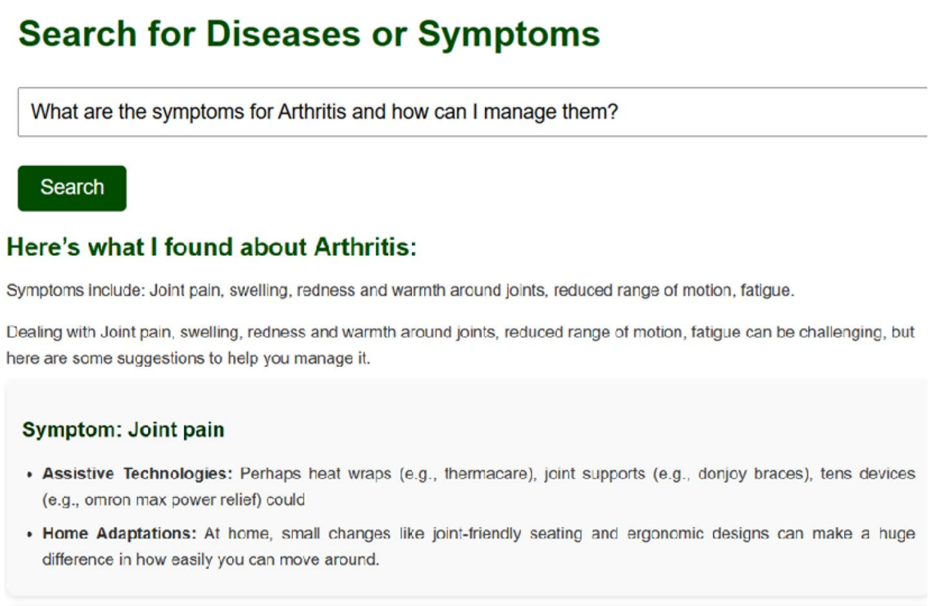

Figure 8. GUI results of the disease and symptom query "What are the symptoms of arthritis and how can I manage them?."

the query, "What are the symptoms of arthritis and how can I manage them?." These results are systematically organized, with symptoms clearly outlined alongside corresponding recommendations. The layout incorporates an appealing interface and succinct descriptions, enabling intuitive navigation and enhancing user interaction. For example, the system suggests practical solutions, sourced entirely from the database, such as "joint supports" for managing "joint pain" or "ergonomic designs" to improve accessibility. These examples demonstrate the system's capability to

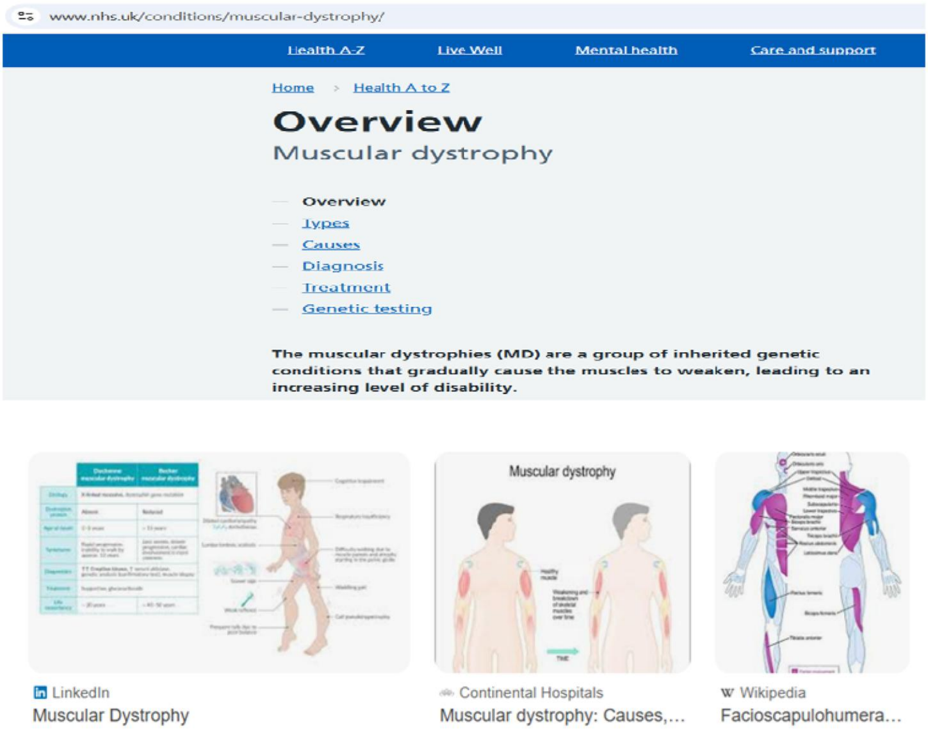

Figure 9. Home-AI provides detailed illustrative and textual data of "Muscular Dystrophy" information from NHS API and external medical databases.

effectively link symptoms with appropriate assistive technologies and environmental adaptations, offering users actionable and relevant strategies to address their individual healthcare needs.

Moreover, the Home-AI system integrates NHS API to ensure credibility and provides query specific tailored images from external medical databases for visual reference as shown in Figure 9. Users can explore more detailed query-specific medical information and its related images through dynamically generated external links. This intuitive and interactive search interface enables personalized, up-to-date, and visually enriched healthcare support, making essential medical knowledge more accessible and actionable.

Despite its strengths, the system encountered challenges in managing ambiguous or overly generic queries. These types of queries often produced less actionable results, requiring additional refinement to fully align with user expectations. The analysis of such cases highlights the need for enhanced context interpretation (Devlin et al., 2019; Sun et al., 2023), enabling the system to better distinguish between specific medical conditions and broader symptom categories, such as differentiating "pain" in general from "pain in the knee," which is more specific to the digestive system or related organs. Nevertheless, even in these instances, the system was able to suggest a variety of assistive technologies and home adaptations to address potential underlying causes of generic queries like "pain."

The Home-AI and ChatDoctor (Li et al., 2023) employed NLP and AI for medical query handling. However, Home-AI enhances the efficiency through FastAPI deployment, fuzzy matching, and personalized healthcare and housing adaptation recommendations for holistic patient support. From a performance standpoint, the system demonstrated an average query response time of 1.8 seconds, effectively providing results in near real-time. This consistent efficiency across diverse queries reinforces the Home-AI's reliability, ensuring a smooth and uninterrupted user experience. By integrating high accuracy in query resolution with an intuitive, user-friendly interface, the system emerges as a robust and transformative tool. It effectively bridges the gap between complex healthcare challenges and practical, personalized solutions, addressing both immediate concerns and fostering long-term improvements in quality of life. These results validate the system's potential as a scalable and adaptable framework capable of addressing a broad range of healthcare-related conversational queries.

Conclusion and future research

Advancements in AI-driven healthcare and housing adaptation solutions are rapidly transforming the way assistive technologies and environmental modifications are recommended for individuals with disabilities. However, many existing models struggle with unstructured medical data, inaccurate matching techniques, and a lack of personalized, context-aware recommendations. This study introduced a novel technological methodology, integrating AI and healthcare for tailored recommendations on disease diagnosis, and associated assistive technologies and home adaptations. The developed system interprets conversational queries using advanced NLP and ML techniques, leveraging publicly available datasets from the NHS and the Mayo Clinic database. The database also include Housing adaptation recommendations guided by WHO's ICF, the ISO 9999:2016 standard for assistive products, and practical guidelines from the Muscular Dystrophy UK Adaptations Manual to enhance safety, accessibility, and overall quality of life. An elaborate multi-tiered query pre-processing architecture, containing exact match, synonym-based match, and fuzzy match query resolution returns personalized recommendation for assistive technologies and home adaptations based on clinical guidelines and best practices, which is quantified using QMA metric with 98% accuracy. Moreover, the language model Google FLAN-T5-small, a transformer-based model enhances the quality of generated recommendations in a context-sensitive and empathetic manner to the user's emotions, for better elocution of conversation. A user-friendly web application powered by FastAPI facilitates an intuitive web interface for the platform and enables real-time statistics. Integrating a user-friendly GUI built with FastAPI, the system renders actionable, personalized healthcare assistance in a comprehensive framework to individuals.

This system represents a significant advancement in AI-driven healthcare, housing, and accessibility, marking a shift from traditional, manual assessments to intelligent, data-driven decision-making. The developed system is highly beneficial for individuals searching for information related to assistive technologies and home adaptations by providing quick, AI-assisted recommendations based on specific diseases and symptoms. By leveraging NLP, fuzzy matching, and LLMs, it enhances the precision and efficiency of information retrieval, allowing users to access tailored recommendations quickly and reliably even in cases where AI models might fail. Moreover, the developed AI-driven DSS allows users to receive instant guidance rather than waiting for consultations. The scalability of FastAPI enables the system to serve a wider audience, such as individuals with disabilities, caregivers, and healthcare professionals with timely and context-relevant recommendations regarding home adaptation and assistive technologies. Moreover, its asynchronous processing capability enables faster response times when compared to traditional appointment-based consultations, thus enhancing efficiency, accessibility, and overall user experience in the delivery of personalized healthcare and housing recommendations using textual and visual references. This is a step change in practice, reducing the burden on OTs and healthcare professionals while ensuring individuals receive well-matched assistive technologies and home adaptations, thus improving independence, reducing wait times, and enhancing the quality of life for those with mobility challenges.

However, despite these achievements, there remains a substantial opportunity for further enhancement, as AI evolves into a new phase of development. The developed system lacks real-time adaptive learning, limiting its ability to update recommendations in response to new studies, user experiences, and medical guidelines. Additionally, the absence of next-generation transformer-based architectures limits its ability to interpret complex semantic relationships within medical data, reducing its contextual awareness. These challenges underscore the importance of deeper integration of AI, in which models better process unstructured medical information, identify complex patterns in the data, and adapt to the changing needs of healthcare.

Overcoming these limitations is a challenge for future studies, as it mainly focuses on using state-of-the-art ML models allowing real-time learning and contextual adaptation. With the coherent amalgamation of advanced LLMs and deep learning techniques, it could enhance the system's ability to interpret user queries and update recommendations in real-time. Scalability improvements will also be sought to serve a greater volume of potentially generalizable queries and to extend coverage to wider areas of healthcare. Incremental innovations in AI will eventually strengthen DSS even further, changing the way care is delivered and experienced on a personal level while increasing access to healthcare and reducing the burden on practitioners. As AI continues to progress, these innovations will further strengthen DSS, making healthcare more accessible, reducing strain on professionals, and ultimately transforming the way individuals interact with personalized care solutions.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the Innovate UK under Grant Application number: 10111890.

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