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ARTIFICIAL INTELLIGENCE IN HOUSING ADAPTATION: A CRITICAL APPRAISAL FRAMEWORK FOR MODERN AI TECHNOLOGIES

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Abstract

This study presents a structured approach to critically appraising research that incorporates artificial intelligence in housing adaptation. It offers a concise overview of the principal AI techniques employed in this domain and addresses key ethical considerations surrounding their use. Recognised reporting standards for AI research are examined to emphasise the importance of transparency and methodological rigour. To support evaluation, ten preliminary questions are proposed to guide the assessment of AI-driven decision support systems applied within the context of housing adaptation.

Keywords Artificial Intelligence, Housing Adaptation, Machine Learning, Generative AI, Digital Twins, Virtual Reality, Augmented Reality, Robotic Process Automation, Smart Homes, Personalised Home Design, AI Ethics, Big Data, Predictive Analytics, Accessibility, Ethical Challenges in AI

Introduction

Artificial intelligence (AI) is increasingly shaping the way housing adaptation is understood and delivered. Research has begun to explore how AI technologies can support more responsive, personalised, and efficient approaches to modifying homes, particularly for individuals with disabilities or age related needs. From predictive algorithms that anticipate future housing requirements (Box 1) to generative design tools that create tailored living spaces (Box 2), AI is no longer a distant concept but an emerging component of practice. These developments have been discussed in recent systematic reviews that map the scope and impact of AI within this field ([1]; [2]).

Despite the optimism surrounding these innovations, AI in housing adaptation must be approached critically. As with any technological intervention, its implementation brings both opportunities and challenges. On one hand, AI may increase precision and speed in design

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decisions. On the other, it raises questions around data privacy, algorithmic bias, and the interpretability of automated decisions. Without careful scrutiny, there is a risk that such systems could unintentionally reinforce inequalities or operate in ways that are not transparent to users or professionals.

This paper sets out to clarify the main uses of AI in housing adaptation and provide tools for critically engaging with the literature. Key concepts are introduced, followed by a discussion of ethical issues that commonly arise when AI is integrated into housing services. Practical resources such as evaluation checklists and reporting guidelines are also highlighted. Finally, a set of initial questions is proposed to help readers assess research focused on AI based decision support systems, one of the most widely used AI applications in this area. These reflections aim to support informed engagement with AI in housing, grounded in both technical awareness and ethical responsibility.

Box 1: Machine Learning for Housing Adaptation

Study: A study developed a predictive model using machine learning to assess the risk of damp in English housing. The model analyzed data from inspection records and building characteristics, including moisture levels, ventilation, and insulation properties, to identify homes at risk. This allows housing managers to prioritize interventions for properties that are more likely to experience damp-related issues, such as mold growth or structural damage. By identifying at-risk properties early, the model enables housing providers to proactively address maintenance needs before they escalate into larger, more costly issues. This approach highlights how AI and machine learning can enhance housing adaptation by improving both the timeliness and efficiency of maintenance interventions, ultimately leading to healthier and safer living environments.

Box 2: Generative AI for Accessible Housing Design

Study: A 2024 paper explored the role of generative artificial intelligence (GenAI) in addressing the housing gap in the U.S. for low-income families. The study examined how GenAI could be applied to generate personalized housing layouts that are fully accessible to individuals with mobility challenges. While the study concluded that AI is not a standalone solution to the broader housing crisis, it emphasized the potential for Generative AI to complement existing strategies by improving the design and affordability of homes for underserved communities. The researchers highlighted that AI could help design homes that are more adaptable to future health needs, and space-efficient, maximizing the usability of smaller units. Recommendations were made for policymakers, developers, and community

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organizations to ensure that AI-driven housing solutions are deployed in a way that is equitable and effective, particularly for low-income families in need of accessible housing.

How does AI contribute to housing adaptation??

Artificial intelligence (AI) is a transformative field of technology, designed to execute tasks traditionally associated with human intelligence. It represents an inherently interdisciplinary domain, drawing upon expertise from computer science, urban planning, architecture, psychology, and related fields.[3]. AI in housing adaptation is divided into two broad categories [4]:

- Artificial Narrow Intelligence (ANI): Refers to machine learning algorithms that can recognise patterns in large datasets. ANI is useful for solving classification and clustering problems in areas such as predicting housing modifications, optimising layouts, and personalising living spaces. It excels at performing a single, well-defined task (e.g., predicting the need for specific housing modifications for individuals with mobility challenges).
- Artificial General Intelligence (AGI): Refers to AI applications capable of reasoning, argumentation, memory, and problem-solving. Artificial General Intelligence (AGI), often termed human-level AI, is characterised by its capacity to exhibit cognitive abilities comparable to those of human beings.. While ANI is already having a major impact in housing adaptation, such as in predictive algorithms for accessibility needs, AGI remains an area of active research and has yet to find robust, widespread applications in practical housing contexts.

Whereas Artificial Narrow Intelligence is already transforming housing adaptation (e.g., predicting the need for wheelchair ramps, optimising smart home designs, and personalising layouts for accessibility), Artificial General Intelligence remains in the research phase and has few practical applications at present.

Also important, but beyond the scope of this discussion, are AI's administrative functions, such as automated systems for resource allocation, predictive maintenance for housing, and AI-driven scheduling tools for construction and modifications.

From a computational perspective, the various uses of AI in housing adaptation can be classified into five broad categories [5]:

- Prediction: Using historical data to predict the likelihood of future housing modifications (e.g., predicting the need for home modifications based on the aging of residents).
- Classification: For example, classifying a house's layout as suitable or unsuitable for accessibility modifications (e.g., identifying which homes require changes for wheelchair accessibility).

- Association: Finding underlying relationships between variables to enhance predictions (e.g., understanding the link between health conditions and specific housing adaptations).
- Regression: A statistical method used to evaluate the strength and nature of the relationship between a dependent variable and one or more independent variables. (e.g., evaluating how the mobility of a resident influences housing modification requirements).
- Optimisation: Mainly applied in administrative tasks, like optimising resource allocation for housing adaptations or project scheduling for home modifications.

Key terms and definitions are provided in the glossary (Box 3), and the following sections offer a more detailed exploration of these categories and associated concepts.

Box 3 | Glossary: Terminology and Definitions (In the Context of Housing Adaptation)

Artificial Intelligence (AI)

AI refers to technology capable of performing tasks that typically require human intelligence. In housing adaptation, AI is used to predict housing modification needs, optimise layouts, and personalise modifications based on residents' health conditions, mobility, and preferences.

AI System

An AI system in housing adaptation incorporates algorithms, hardware, and software platforms designed to predict, analyse, and recommend housing modifications such as accessibility improvements, adaptive design features, and environmental optimisations.

Big Data

Big data involves large datasets that require special technologies and analytical methods to be transformed into value. In housing adaptation, big data can be used to analyse patterns in resident behaviours, building characteristics, and environmental factors to predict and optimise future housing needs.

Calibration and Miscalibration

Calibration refers to the degree to which the predicted probabilities generated by an AI model correspond with actual observed outcomes. Miscalibration arises when this alignment is inaccurate, for example, when the model underestimates the need for specific housing adaptations as a result of incomplete or biased training data.

ChatGPT

Chat Generative Pre-trained Transformer, a conversational AI tool that can be used in housing adaptation to gather input from residents, provide modification recommendations, or assist in explaining housing solutions for accessibility or personalisation.

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Cloud Computing

The on-demand availability of computing resources over the internet. In housing adaptation, cloud computing allows for scalable data storage and processing, enabling the deployment of AI models that predict housing modification needs or optimise layouts in real time.

Computer Processing Power

The ability of a computer to process information at speed. In housing adaptation, strong processing power is required to run complex models that analyse large datasets, such as those predicting residents' future needs for home modifications.

Conversational AI

AI systems designed to engage in dialogue with users. In housing adaptation, conversational AI can help residents interact with smart home devices or communicate their housing needs, such as requesting specific modifications or adjustments to home layouts.

Data Leakage

Occurs when some of the data used for training is inadvertently included in the testing or validation sets, leading to inflated model performance. In housing adaptation, data leakage could result in overoptimistic predictions about housing needs, potentially leading to ineffective modifications.

Deep Learning

A subset of machine learning using multi-layered artificial neural networks to learn from large datasets. In housing adaptation, deep learning can help optimise designs for accessibility and predict future modification needs based on historical data and resident characteristics.

Data Poisoning

A type of attack where misleading data is deliberately introduced into a training set. In housing adaptation, data poisoning could lead AI systems to make poor or biased recommendations, such as incorrectly predicting the need for home modifications.

Fairness

Fairness refers to the principle that AI systems should treat individuals equitably, ensuring that outcomes are free from unjust or systematic discrimination. In housing adaptation, fairness ensures that AI-driven systems do not disproportionately affect certain groups (e.g., low-income or disabled residents) when making recommendations for housing modifications.

Generative AI

Generative AI describes a class of algorithms designed to produce new content by learning and replicating patterns derived from existing data.. In housing adaptation, generative AI can design

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customised home layouts or suggest modifications based on a resident's personal needs and preferences, such as accessibility features or space optimisation.

Intended AI Use

The specific purpose for which an AI system is designed. In housing adaptation, this refers to AI being used to predict and design modifications to accommodate residents' needs, whether for accessibility, comfort, or environmental efficiency.

Large Language Models (LLMs)

AI models that process and generate human-like text. In housing adaptation, LLMs can generate reports, user-friendly communication, or interactive dialogue that helps residents understand their housing needs and modification options.

Large Multimodal Models (LMMs)

AI models that accept and process multiple types of input data (e.g., text, images, video). In housing adaptation, LMMs could combine information from blueprints, resident feedback, and environmental factors to generate home designs or modification recommendations.

Machine Learning

A type of AI where models learn patterns from data. In housing adaptation, machine learning is used to predict necessary modifications based on resident data (e.g., health conditions, mobility needs) or environmental changes (e.g., climate-induced modifications).

Reinforcement Learning

A type of machine learning where an agent learns to make decisions based on feedback and trial and error. In housing adaptation, reinforcement learning could be used to optimise decision-making in resource allocation for modifications, ensuring that resources are used effectively to meet residents' needs.

Supervised Learning

A type of machine learning where the algorithm learns from labelled data. In housing adaptation, supervised learning can be used to predict modification needs, such as wheelchair ramps or bathroom adaptations, based on historical data and specific resident characteristics.

Unsupervised Learning

A type of machine learning where the algorithm identifies patterns in unlabelled data. In housing adaptation, unsupervised learning can be used to detect hidden patterns, such as clusters of residents with similar modification needs or behavioural trends that could inform future housing projects.

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Zero-Shot Learning

The ability of an AI model to make predictions about new, unseen data without needing additional training. In housing adaptation, zero-shot learning could be used to predict modification needs for new residents, even if there is limited historical data available.

Virtual Reality (VR)

Virtual Reality (VR) is a technology that immerses users in a computer-generated, simulated environment, typically experienced through specialised headsets and sensory interfaces. In housing adaptation, VR can be used to visualize home modifications before they are made, allowing residents and designers to explore potential modifications and layouts in a 3D space. It can also be used for training housing professionals on accessibility standards or to simulate different living scenarios based on resident needs.

Augmented Reality (AR)

Augmented Reality (AR) overlays digital information onto the real world. In housing adaptation, AR can be used to help residents and architects visualize housing modifications in real-time, such as overlaying proposed wheelchair ramps or wider doorways onto existing floor plans during the design phase.

Big Data

Big data refers to large, complex datasets that cannot be analysed efficiently using traditional tools. In housing adaptation, big data includes information from diverse sources such as building characteristics, environmental factors, resident demographics, and social conditions. As the amount of data used in housing management continues to grow, conventional tools like spreadsheets are no longer sufficient for processing the complexity of this information. Cloud computing and advances in computer processing power are central to enabling AI technologies, allowing for real-time analysis and facilitating better decision-making in housing modifications.

An example of big data in housing adaptation could be a platform like SmartHousing, which integrates data from smart home systems, environmental sensors, and resident feedback. Such platforms allow housing providers to make informed, data-driven decisions regarding home modifications, such as predicting which properties need accessibility improvements or energy efficiency upgrades. These systems analyse various data points, like energy consumption, mobility data, and user preferences, to forecast future housing needs, ensuring that the modifications made are both cost-effective and tailored to the residents' evolving requirements.

Research by [6] in the context of rental housing platforms highlights the importance of big data in shaping housing markets. Their work discusses how platforms like Airbnb collect and use

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vast amounts of housing data to influence market trends, availability, and pricing. Similarly, housing adaptation could benefit from big data by predicting long-term housing trends and modifying existing structures to meet changing needs, such as the growing demand for accessible homes.

Additionally, AI technologies, which rely heavily on big data, can personalise housing modifications to meet specific resident needs. For instance, Generative AI can be used to design custom layouts for homes, optimising space for residents with particular accessibility needs or predicting future modifications based on resident data, environmental changes, or demographic trends. [7] highlight how digital tools and AI can improve the design and efficiency of affordable housing, which could be applied to adaptive housing solutions.

Machine Learning: Many Current Benefits

Machine learning is a subtype of AI where models or algorithms learn patterns from data rather than being programmed with explicit rules [8]. Various types of machine learning algorithms exist, some of which overlap, including supervised learning, unsupervised learning, reinforcement learning, deep learning, and zero shot learning (see Box 3 for definitions and Box 1 for an example). In the context of housing adaptation, machine learning can be used to predict housing modification needs, optimize home designs, and personalize modifications based on resident data, such as health conditions, preferences, and environmental factors.

Machine learning models in housing adaptation can significantly enhance decision making by analyzing vast amounts of data, such as building characteristics, environmental conditions, and the specific needs of residents. For example, supervised learning models [9] could predict the need for specific housing modifications and prices based on past data, while unsupervised learning [10] could help identify clusters of residents with similar housing needs. Reinforcement learning [11] could be used to optimize resource allocation for home adaptations, ensuring that available resources are used efficiently.

However, machine learning applications in housing adaptation also face challenges such as [12] data leakage, undercutting, and data poisoning issues that can lead to inaccurate predictions and suboptimal housing modifications. Data leakage, for instance, occurs when information from the testing set inadvertently influences the model, leading to overly optimistic results. In housing adaptation, this could happen if data on existing housing modifications, such as home accessibility features, is improperly used in training predictive models, causing models to perform better in tests than in real world scenarios. Similarly, biased samples such as focusing only on properties in urban areas with higher income residents could lead to faulty recommendations that do not apply to broader populations, potentially leaving out the most vulnerable residents or leading to inefficient adaptations.

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Addressing these challenges is essential to ensure that machine learning models in housing adaptation provide reliable and equitable outcomes for all residents, particularly those with specific needs such as mobility impairments or low income households.

Generative AI and Its Potential for the Future in Housing Adaptation

Generative AI includes technologies such as large language models (LLMs) and large multimodal models (LMMs). LLMs are AI systems trained on extensive corpora comprising billions of words from books, articles, and other text-based online content, enabling them to generate human-like language. LMMs build upon this by accepting a wide range of input types, including text, images, audio, video, and, in some cases, sensory data. These models can produce outputs in formats different from the input; for example, an image may result in a textual description, or a text prompt may generate a visual representation, demonstrating significant cross-modal capability. In the context of housing adaptation, these AI systems can generate suggestions for optimal home layouts, propose personalised accessibility modifications, and assist in redesigning spaces to meet the unique needs of individuals, much like how these technologies are used in other fields for decision making and generating outputs.

LLMs and LMMs are increasingly used in various sectors, including housing, to retrieve knowledge, support design processes, summarise key findings, and triage housing-related issues. A recent study examined the extent to which large LLMs represent or "encode" knowledge, highlighting their current limitations and offering recommendations for future research directions. These AI models have the potential to assist architects, urban planners, and housing developers by providing data-driven insights into how housing adaptations can be tailored for accessibility, sustainability, and optimal space use.

An inherent limitation of LLMs and LMMs is their tendency to produce inaccurate or fabricated information, a phenomenon commonly referred to as "hallucination" [13] (e.g., provide recommendations that are not based on real data or cite inaccurate sources). In housing adaptation, this could manifest as AI suggesting design features that may not be practical, safe, or compliant with local regulations. LLMs are also vulnerable to data poisoning, where corrupted data results in flawed recommendations. In the housing context, this could mean the AI suggests modifications that are unsafe or not beneficial for residents, leading to potentially harmful outcomes.

One example of an LLM in use is ChatGPT (Chat Generative Pre-trained Transformer), which has been applied to address common housing-related queries. These include advice on adaptive design for wheelchair accessibility and information regarding building regulations relevant to individuals with mobility impairments. Owing to their conversational interface, both LLMs and LMMs can simulate human-like interaction, allowing users to pose questions, receive responses, and provide feedback in an iterative manner. Furthermore, as these models are

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designed to interpret and incorporate contextual information rather than relying solely on discrete inputs, they have the potential to tailor responses according to individual resident preferences and communication styles. Their capacity to deliver information in a user's preferred language further enhances both accessibility and overall usability.

Thus, generative AI could potentially overcome some of the limitations of previous generations of housing adaptation tools and help humanise the interface between residents and housing systems. Although some housing providers are already experimenting with tools such as ChatGPT for resident queries and design suggestions, at the time of writing, the full potential benefits are still under exploration rather than being widely realised.

Digital Twins in Housing Adaptation

A **Digital Twin** is a highly sophisticated digital representation of a physical entity, system, or process. This virtual model acts as a dynamic mirror of its physical counterpart, enabling real-time simulations, analysis, and optimization. Digital Twins in housing adaptation [14] serve to create dynamic, real-time models of residential environments, incorporating factors such as environmental conditions, occupant health data, and the wear-and-tear of household systems. These digital models allow housing providers and individuals to experiment with different adaptations and predict their outcomes before actual physical changes are made [15].

The key advantages of utilizing Digital Twins for housing adaptation include:

- Real-time monitoring: Digital Twins continuously monitor the condition of homes and their systems, such as heating, ventilation, and air conditioning (HVAC), plumbing, and electrical systems. This data allows housing providers to identify issues and plan for necessary maintenance or modifications based on the real-time condition of the house, improving efficiency and reducing costs [16].
- Predictive capabilities: By integrating predictive analytics, Digital Twins can forecast future changes, such as wear-and-tear on systems or potential safety hazards. This helps anticipate the need for modifications, making it possible to plan for housing adaptation based on projected trends, such as aging-in-place needs.
- Optimizing energy efficiency: These models also enable testing of energy-efficient measures before implementation. For example, adjusting the home's insulation or switching to more energy-efficient appliances can be simulated to analyze their effects on energy consumption, helping to reduce energy bills and environmental impact [17].

Virtual Reality (VR) and Augmented Reality (AR) in Housing Adaptation

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VR and AR are pivotal in the conceptualization and visualization of housing adaptations. These technologies allow stakeholders, including residents, architects, and contractors, to engage with the space and the proposed changes in highly interactive ways.

- VR: With VR, individuals can immerse themselves in a completely virtual version of their modified home. For example, a person with mobility impairments can virtually navigate through a wheelchair-accessible home and experience firsthand whether the modifications meet their needs. This immersive approach provides a tangible feel for how changes will impact space usage, reducing uncertainties before physical work begins [18].
- AR: Unlike VR, which is fully immersive, AR overlays digital information onto the physical environment. This makes AR particularly useful during the design and planning stages of housing adaptations. Architects and contractors can visualize proposed changes, such as where a new ramp or a wider doorway might fit, by seeing these changes overlaid on the actual physical space in real-time. This helps in making design decisions more efficiently and accurately [18].

These technologies help bridge the gap between abstract design concepts and real-world implementation, ensuring that the adaptations are not only functional but also user-friendly and aligned with the residents' needs.

Robotic Process Automation (RPA) in Housing Adaptation

Robotic Process Automation (RPA) plays a crucial role in streamlining the administrative aspects of housing adaptation. RPA refers to the use of software bots to automate repetitive and time-consuming tasks, such as processing paperwork, coordinating services, and tracking progress. This reduces the burden of administrative tasks on housing professionals, [19] allowing them to focus on more critical aspects, such as ensuring the quality of the housing modifications.

- Automating paperwork and compliance: In housing adaptation, RPA can handle tasks such as filling out forms for government assistance programs, tracking compliance with building codes, and submitting modification requests. This significantly reduces human error and ensures that all legal and regulatory requirements are met in a timely and efficient manner.
- Coordinating services: Housing adaptations often involve multiple contractors, service providers, and government agencies. RPA can automate communication and scheduling among these parties, ensuring that tasks are completed on time and according to plan.
- Progress tracking: RPA can also monitor the progress of housing modifications, providing real-time updates to stakeholders and ensuring that any delays or issues are addressed quickly. This transparency and automation reduce the likelihood of errors or miscommunication during the adaptation process.

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Ethical Challenges of AI Applications in Housing Adaptation

The output of an AI system is directly influenced by how it is developed, echoing the well-known phrase "rubbish in, rubbish out" (Vibbi, 2024). Systems trained on low-quality data are more prone to producing biased results. In housing adaptation, examples of poor-quality data include missingness (when essential variables, such as accessibility needs or tenant preferences, are not recorded), non-representativeness (when key population groups intended to benefit from the AI system are absent or significantly underrepresented), and misclassification (when incorrect assumptions are embedded in the data regarding tenants or users).

As a result, AI systems may perform more accurately for individuals who are well-represented in the training data, while yielding less reliable results for those who are not. Over time, this can lead to uneven outcomes that disadvantage already marginalised populations, such as low-income tenants or individuals with disabilities.

Mitigating the effects of bias in AI systems presents significant challenges, as bias can emerge at various stages of the development process. It may originate in the training data, but can also be introduced during model design or after deployment. For instance, bias may result from the selection or weighting of specific variables, such as giving precedence to one type of housing modification over others. It can also arise during implementation due to interaction with existing societal biases, such as conscious or unconscious discrimination by housing professionals, or through changes in the data or population over time. This includes scenarios where the data used in real-time housing decisions evolves or where the demographic characteristics of the target population shift. These dynamics underline the importance of continuously monitoring AI systems after deployment to ensure reliable and equitable performance in housing adaptation.

The ethical implications of AI extend beyond concerns about bias. Despite their data processing capabilities, AI systems lack genuine understanding of context and meaning. In housing adaptation, elements such as empathy, recognition of individual needs, and the creation of inclusive environments are likely to remain essential human responsibilities. As highlighted in recent discussions on generative AI, these models are not inherently concerned with the truth or relevance of their outputs. This is a key reason why AI tools are primarily designed to support, rather than replace, trained professionals.

The responsible use of AI in housing adaptation also requires human attributes such as humility and critical judgement. Messeri and Crockett, in a recent review, described four common conceptual roles attributed to AI systems: oracle, arbiter, quant, and surrogate. They warned of several cognitive pitfalls linked to these roles, including the illusion of explanatory depth (believing an AI-generated explanation is more insightful than it is), the illusion of exploratory

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breadth (assuming the system has considered a full range of options when it has not), and the illusion of objectivity (assuming the output is free from bias despite underlying data limitations).

For these reasons, ethical considerations and human rights must be embedded throughout the development and application of AI technologies. Within the context of housing adaptation, this approach is essential to ensure that AI systems promote fairness, accessibility, and inclusivity. The European Commission, along with other AI-focused organisations, has endorsed six core ethical principles for the responsible use of AI in housing (see Box 4), which offer critical guidance for ethical implementation.

Box 4 | Ethical Principles for AI Use in Housing Adaptation

The following six key ethical principles should be considered in the design, development, and use of AI tools in housing adaptation:

1. Transparency: AI systems should be transparent in their decision-making processes, allowing residents and housing providers to understand how decisions are made.
2. Accountability: Developers and housing providers should be held accountable for the outcomes of AI-powered decisions, ensuring they remain responsible for actions that affect residents.
3. Fairness: AI systems must be designed to be equitable and inclusive, ensuring they do not discriminate against any group, particularly vulnerable or marginalised populations.
4. Privacy: Residents' privacy should be protected, and their data should be handled securely and used only for its intended purpose.
5. Human-Centered Design: AI tools should be designed to complement human decision-making, ensuring that residents' needs and preferences are at the centre of any housing solutions provided.
6. Continuous Monitoring: The performance and impact of AI systems should be regularly evaluated and adjusted to ensure they continue to benefit all stakeholders, particularly vulnerable populations.

These ethical principles are essential to ensuring that AI systems in housing adaptation are developed responsibly and equitably.

Box 5 presents ten key questions to consider when critically appraising a study describing the use of AI in decision support for housing adaptation. While these questions are framed within this specific context, many are applicable to other forms of AI tools and applications. In formulating these questions, we drew upon several established AI quality assessment frameworks and reporting guidelines (Berggren et al., 2021).

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Even if a structured critical appraisal using the questions in Box 5 indicates that the study was conducted rigorously and yields trustworthy results (i.e., strong internal validity), an additional consideration is whether the AI intervention is effective in real-world housing practice (i.e., external validity). For example, the residents requiring adaptations may differ meaningfully from the population on which the AI model was originally trained. Similarly, housing providers or technical professionals implementing the intervention may operate under different conditions or possess different skills than those involved in the original study. These contextual differences can influence how well the AI system performs in practice.

Box 5 | Ten questions to ask about a paper that reports an AI-Based Decision Support System for Housing Adaptation

1. What was the study design, and does it meet recognised standards of methodological rigour, excluding AI-specific aspects?
Studies involving AI in housing adaptation should follow sound research methodology. This includes the use of appropriate designs, sufficiently large and representative samples, and clear justification of chosen methods. If a randomised controlled trial would have been appropriate for the research question, was one conducted? If not, are the limitations of the alternative design clearly explained? Did the participant sample reflect the broader population with housing needs? Where comparisons were made between intervention and control groups, were baseline characteristics such as age, family structure, and disability status comparable? Consider both the individuals whose data were used to train the AI system and the end-users who interacted with the system, including how they were introduced to the technology.
2. What was the intended function of the AI system, including the decisions it was designed to support, who was expected to use it, and for what purpose?
The role of the AI tool should be clearly defined. For example, the system may be designed to support housing officers or contractors in identifying suitable modifications for residents with mobility challenges, with the objective of improving the speed and relevance of decision-making.
3. What type of computational task was the AI system developed to perform?
It is important to specify whether the AI system was built for prediction, such as estimating the likelihood that a home requires adaptation; classification, such as categorising properties by accessibility needs; association, such as identifying relationships between housing features and user satisfaction; regression, such as estimating the cost of adaptations; or optimisation, such as enhancing the efficiency of design and decision processes.
4. What AI system was used, and in what way was it applied?
A clear description of the AI model is necessary, including its algorithmic approach, version,

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and any relevant hardware or software. The source of the data used for training and input should be explained, including how it was collected, prepared, and managed. The study should address how missing or low-quality data were handled and describe how outputs were presented to the users, as the format of output delivery can significantly influence user interpretation and engagement.

5. Where in the housing adaptation process was the AI system introduced?
The timing of AI recommendations can influence decision-making. If users received AI guidance alongside other information, it may have introduced cognitive biases. Alternatively, if recommendations were received after an initial decision, they may have prompted re-evaluation. The study should report when and how the AI system was integrated into the workflow.
6. How were errors managed, and were any safety concerns or adverse events reported?
The study should describe its approach to identifying and addressing errors. These may include algorithmic errors, such as generating inappropriate recommendations; system-related issues, such as failure to produce outputs due to technical faults; and user errors, such as incorrect data entry or misuse of the system. Safety monitoring should be ongoing and account for potential harms that may only emerge after deployment in real-world settings.
7. How did the study address human factors that influence the use of the AI system?
Human factors, including workload, familiarity with technology, trust in automation, and the potential for stress or cognitive overload, can significantly affect how users engage with AI. The study should explore how the design of the AI system supported or hindered effective interaction with users and whether any measures were taken to assess and improve usability.
8. How transparent were the authors about the data and code used for model training and validation?
The study should provide a clear and accessible explanation of the datasets, including any documentation such as data sheets. This helps non-technical readers understand the structure and purpose of the data. Where possible, code used for training and validating the model should be made available, for example as supplementary material.
9. How did the study address ethical concerns related to the AI system?
The authors should explain how they assessed and managed issues such as bias in model outputs, data privacy, and information security. The study should also describe whether residents were provided with clear information about the AI system and how it was used, ensuring that users could give informed consent or understand its implications for their housing adaptations.

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10. Was the research informed by multidisciplinary expertise? AI systems in housing adaptation benefit from input across fields including housing, architecture, disability services, technology, and ethics. The study should describe whether diverse forms of expertise were incorporated into the design, development, and evaluation of the AI system, and how this influenced the overall quality and relevance of the research.

Reporting Guidelines for AI Studies in Housing Adaptation

While numerous reporting guidelines and checklists exist for studies involving AI, there remains a lack of validated quality appraisal tools specifically tailored to the field of housing adaptation. Although there is growing publication guidance on what information authors should report when describing AI applications in this context, tools for systematically evaluating the quality of such reports are still underdeveloped.

Many of the available checklists are intended to support readers in appraising AI research, focusing not only on the completeness of reporting but also on whether each element has been addressed to an acceptable standard. However, these guidelines should be applied judiciously. They are not intended to serve as definitive quality checklists, and inappropriate use may lead to oversimplified or inaccurate evaluations.

The selection of the appropriate reporting guideline should be based on the specific study design under review. For instance, AI-based decision support systems developed for use in housing adaptation require appraisal frameworks that reflect the multifaceted nature of housing interventions. This includes consideration of technical performance, user context, and the social and environmental complexities inherent in adaptive housing solutions.

ECOAI, for instance, is an AI system designed to predict energy efficiency upgrades for low-income housing. The system should have transparent reporting on how the algorithm was trained on data related to the types of homes in that region, and how it accounts for local building standards. This system might analyse factors such as building materials, geographical location, and the age of the building to make recommendations for energy-saving improvements such as insulation, window replacements, or HVAC system upgrades. ECOAI helps ensure that energy-efficiency recommendations are appropriate for the building and community context.

Another example is AccesSmart, an AI system that optimises accessibility in homes for elderly or disabled residents. It recommends modifications like ramps, wider doorways, or accessible bathrooms. The reporting would need to detail how the algorithm factors in specific resident needs (e.g., wheelchair users, visually impaired residents) and how these housing adaptations are prioritised based on the individual’s condition. AccesSmart provides an intelligent way of

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assessing and recommending tailored housing modifications, improving residents' mobility and independence.

Additionally, HomeAI integrates smart-home technologies to assist with housing adaptations. For instance, HomeAI might evaluate the daily routines of elderly residents and use sensor data to suggest real-time modifications, such as automatic lighting adjustments, motion sensors for safety, or voice-activated control for appliances. The AI system would also learn from these routines over time, evolving its recommendations based on residents' changing needs. This system ensures that housing remains adaptable and responsive to the evolving needs of residents, enhancing their quality of life.

Finally, researchers are exploring systems like RuralHomeAI, specifically designed for rural housing adaptation. Unlike traditional models, RuralHomeAI accounts for the unique needs of rural homes, where space, building materials, and environmental factors may differ significantly from urban settings. For example, in rural areas, the AI model might prioritise outdoor modifications such as ramps or assess energy efficiency using renewable energy sources like solar panels, which are more common in rural settings.

These examples, such as ECOAI, AccesSmart, HomeAI, and RuralHomeAI, demonstrate the wide range of applications AI can have in housing adaptation, from improving energy efficiency to making homes more accessible and smart. Evaluating these AI systems requires robust reporting guidelines to ensure they are transparent, effective, and equitable. As the field of AI continues to evolve, ensuring that these tools meet high standards will be crucial to their successful integration into the housing sector.

Conclusions

AI has significant potential in housing adaptation. However, AI is not a one-size-fits-all solution, and the risk of bias remains a concern in AI studies. A structured approach, based on a set of critical questions to evaluate AI-driven decision support systems, will help housing professionals distinguish between robust and valuable AI tools and those that offer limited benefit, potentially exacerbate inequalities, or even cause harm. Ensuring that AI applications are transparent, unbiased, and tailored to the specific needs of residents is essential for maximizing their impact in improving housing quality, accessibility, and sustainability.

Declarations

Consent to Participate
Not applicable. This study did not involve direct interaction with human participants.

Consent to Publish
Not applicable.

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Ethics Statement

This research did not involve human participants, animals, or the use of sensitive data. Therefore, ethical approval was not required in accordance with accepted research standards.

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Data Availability

Not applicable. No datasets were generated or analyzed during the current study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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