SGVU International Journal of Environment, Science and Technology

Journal homepage: https://www.gyanvihar.org/researchjournals/envirmental_science.php

E-ISSN: 2394-9570

Vol. 12 Issue 1 Page No 53 - 78

Review article

Review of AI Systems for Human Behaviour Prediction in Smart Environments

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Keywords

Human Behaviour Prediction, Smart Environments, Artificial Intelligence (AI), Multimodal Sensing, Context-Aware Computing.

Abstract

Smart environments that integrate sensors, IoT devices, and intelligent computing have significantly advanced the ability to model and predict human behaviour across various settings like homes and hospitals. This review analyses 28 studies from 2007 to 2025, categorizing methods into generative models, deep learning, reinforcement learning, and traditional machine learning. Innovations using RNNs, transformers, GANs, and explainable, human-in-the-loop systems have improved adaptability and interpretability, while technologies like digital twins and neuromorphic computing enable real-time, multi-user behaviour prediction. However, challenges such as limited datasets, privacy issues, high computational costs, and poor generalization remain. Proposed solutions include ethics-focused design, zero-shot learning, and federated learning to drive the development of more intelligent, flexible, and human-centred systems..

INTRODUCTION

Smart environment has experienced significant development recently, in great part thanks to the application of artificial intelligence (AI). The evolution from systems automating repetitive tasks has led to a vibrant, dynamic field centred on developing user-aware, adaptive ecosystems. Such environments are increasingly used for service personalization, optimizing energy use and wellbeing in homes, hospitals, and infrastructures (Cook & Das, 2007; Ramos et al., 2008).

A key component of this evolution is the system's capacity to understand and predict human activity. Using various sensor inputs, from motion detectors to audio and video. Analyzing this data with machine learning techniques makes it possible for systems to notice patterns in their users' behaviours and to adapt their responses. For instance, a smart thermostat could learn the routine of a person living in a home and automatically adjust temperatures, or a health-monitoring system could notice early cues about a person's well-being from movement or voice patterns (Yang et al., 2018; Stoffel et al., 2025).

Previous works in this area were mostly based on simple rule-based or statistical approaches. Although foundational, these typically were applied in a very limited way and found not to be able to handle complex or unpredictable behaviour, in particular within shared, changing environments (Crandall & Cook, 2009; Cook & Das, 2010). Recent studies have focused on data-driven models, particularly those that use deep learning and reinforcement learning. Those models are much better at spotting subtle or non-linear patterns of behaviour (Choi et al., 2013; Kumar, 2025). That's led to more reliable and scalable systems. Some of those are already being used in mental health monitoring, energy management, and telemedicine (Zhang et al., 2025; Faisal et al., 2025).

As these systems improve, they raise significant concerns regarding the accuracy and fairness of their predictions. There is a growing need to trust that the predictions they make are both reliable and unbiased. Additionally, protecting users' privacy is crucial, particularly when dealing with sensitive and personal information. These concerns have led to increased interest in explainable AI (XAI) and human-in-the-loop strategies, which aim to make AI decision-making more transparent and empower users to participate in the process (Jo et al., 2025; Karlsson & Kayembe, 2025). In fields such as healthcare and assisted living, these considerations are not merely technical; they represent fundamental ethical imperatives (Ramezani et al., 2025; Boldo, 2025).

This review aims to provide a comprehensive and systematic overview of AI-driven human behaviour prediction in smart environments. It charts the journey of this field from its early experimental stages to the cutting-edge applications we see today, driven by sophisticated machine learning. The paper also sheds light on current hurdles, like data integration, real-time responsiveness, and personalization, and investigates new avenues such as neuromorphic computing and sustainable AI (Almeida et al., 2022; Nie et al., 2025; Ye et al., 2025; Tinarelli et al., 2025).

Ultimately, the aim is to equip both researchers and practitioners with a deeper insight into the possibilities and challenges of creating intelligent environments that are not just efficient but truly aware of human needs.

1.1 Background and Significance of Human Behaviour Prediction in Smart Environments

The rapid expansion of the Internet of Things (IoT) and ambient intelligence technologies has transformed everyday spaces into interconnected, context-aware environments capable of sensing and responding to human presence and activity (Ramos et al., 2008; Cook & Das, 2010). In this evolving landscape, behaviour prediction has emerged as a cornerstone for delivering personalized services across diverse domains, including healthcare monitoring, smart home automation, elderly care, and energy efficiency (Faisal et al., 2025; Stoffel et al., 2025). These applications rely heavily on accurate and timely recognition of human behaviour to enable adaptive system responses that enhance user comfort, safety, and sustainability. The convergence of artificial intelligence with ubiquitous computing has made it possible to interpret complex, multimodal data streams in real time, thereby supporting dynamic, user-centric environments (Jo et al., 2025; Yang et al., 2018). As these technologies continue to mature, behaviour prediction will play an increasingly vital role in creating intelligent environments that are not only automated but truly responsive to human needs.

Gaps in Traditional Monitoring and Behaviours Recognition Systems

Traditional behaviour monitoring systems in smart environments have largely depended on rule-based logic or simple statistical models, which often fail to capture the complexity and variability of real-world human behaviour. These systems are typically limited in adaptability and struggle in multi-resident settings, where overlapping activities and diverse routines create ambiguity (Crandall & Cook, 2009; Cook & Das, 2010). Moreover, static models cannot learn from new patterns or adjust to evolving behaviours over time, making them unsuitable for dynamic, long-term applications. The inability to integrate and interpret multimodal data, such as voice, gesture, and physiological signals, further restricts their effectiveness in delivering personalized, context-aware responses (Almeida et al., 2022; Choi et al., 2013). As a result, there is a clear need for more flexible, learning-based approaches that can overcome these limitations and support more nuanced, accurate behaviour recognition in increasingly complex smart environments. Table 1 illustrates the historical adoption scores of various behaviour monitoring models, highlighting the shift towards more advanced techniques.

Figure 1 presents a general outline of the review's structure.

S.N.	Year	Rule-Based / Statistical Models	Machine Learni Models	Deep Learning Models
1	2009	85	30	10
2	2010	80	45	20
3	2013	70	60	40
4	2018	55	75	65
5	2022	40	85	80
6	2025	25	90	95

Table 1: Adoption Scores of Behaviour Monitoring Models in Smart Environments (2009–2025);(Crandall, A. S., et.al., 2009);(Cook, D. J., et.al., 2010);(Choi, S., et.al., 2013);(Yang, W., et.al., 2018);(Zhang, L., et.al., 2025)

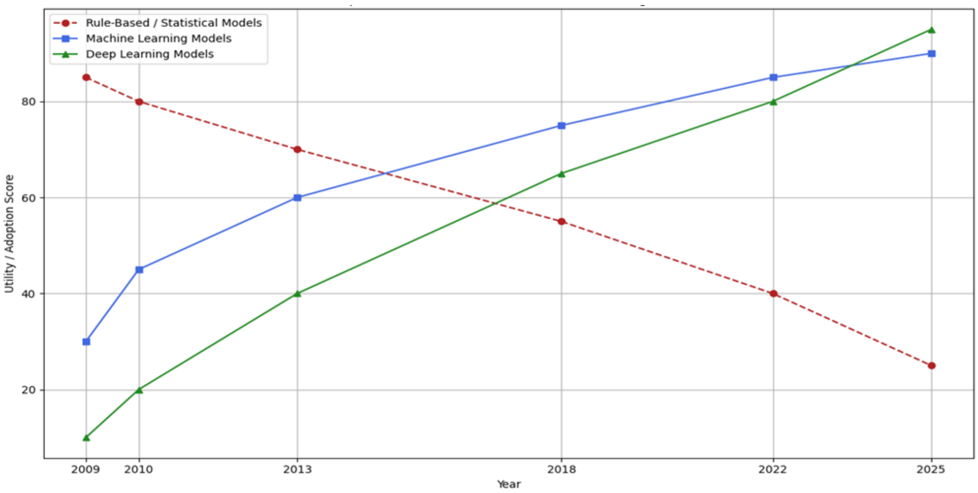

Figure 1: Model Adoption Trends in Human Monitoring (2009-2025)

Rise of Artificial Intelligence in Ambient and Context-Aware Systems

The integration of artificial intelligence into ambient and context-aware systems has significantly advanced the capacity of smart environments to deliver real-time, predictive intelligence. Machine learning and deep learning models have become instrumental in processing vast, multimodal data streams, enabling systems to recognize patterns and anticipate user behaviour with increasing precision (Choi et al., 2013; Kumar, 2025). Sensor fusion plays a pivotal role in this process by combining inputs from diverse sources, such as visual, auditory, and physiological sensors, to enhance contextual understanding, while edge computing facilitates low-latency processing directly at the data source (Yang et al., 2018; Watanabe et al., 2025). In parallel, emerging techniques like generative AI and self-supervised learning are redefining behaviour modeling by allowing systems to learn from unlabelled data, offering scalable and adaptive solutions for behaviour prediction without extensive manual intervention (Jo et al., 2025; Nie et al., 2025). These developments mark a shift toward more autonomous, self-improving smart environments that can adapt continuously to evolving user needs.

Research Goals and Scope

The primary goal of this research is to present a comprehensive review of artificial intelligence (AI) models employed for human behaviour prediction within smart environments. This includes an in-depth comparison between traditional methods, such as rule-based systems and statistical models, and modern AI approaches like deep learning, reinforcement learning, and generative models (Cook & Das, 2010; Choi et al., 2013; Kumar, 2025). The study explores how these evolving techniques have improved adaptability, accuracy, and contextual awareness in applications ranging from smart homes and healthcare to energy management and elder care (Faisal et al., 2025; Stoffel et al., 2025). In addition to mapping existing technologies, this review identifies key challenges such as scalability, personalization, and data privacy, while also discussing emerging trends like neuromorphic computing, explainable AI, and self-supervised learning (Jo et al., 2025; Ye et al., 2025). By integrating technical insights with practical use cases, the paper aims to guide future research and development in designing intelligent, responsive, and ethical behaviour-aware systems.

Overview of Smart Environments and Behaviour Prediction

Smart environments are intelligent spaces equipped with sensors, computational devices, and communication networks that work together to monitor and respond to human presence and activity. Their core purpose is to improve the quality of life through automation, personalization, and context-aware services (Cook & Das, 2010; Ramos et al., 2008). A crucial capability within these systems is behaviour prediction—the ability to analyze patterns in user activity and anticipate future actions. This function enables proactive system responses, such as adjusting environmental conditions or alerting caregivers in healthcare settings (Yang et al., 2018; Stoffel et al., 2025). Advances in artificial intelligence have greatly enhanced these systems, allowing them to interpret complex, multimodal data and evolve beyond rule-based automation to adaptive, real-time decision-making (Choi et al., 2013; Almeida et al., 2022).

2.1 Defining Smart Environments and Ambient Intelligence Systems

Smart environments are technology-enhanced spaces embedded with interconnected devices capable of sensing, computing, and acting upon user behaviour in real time. These systems are designed to deliver personalized, adaptive services by collecting contextual data through sensors, processing it using computational intelligence, and triggering responsive actions, such as adjusting lighting, temperature, or providing alerts (Cook & Das, 2010; Ramos et al., 2008). Key features of smart environments include environmental and behavioural sensing, edge or cloud-based computing, actuator-driven feedback, and user-specific personalization. These capabilities are exemplified in real-world applications like smart homes that automate daily routines, smart hospitals that monitor patient activity, and smart offices that optimize energy and space usage based on occupancy and behaviour (Tinarelli et al., 2025; Faisal et al., 2025). At the core of these systems lies the concept of ambient intelligence, which emphasizes seamless human-computer interaction and anticipatory system behaviour designed around users' needs.

Human Behaviour and Activity Types in Smart Spaces

In smart environments, human behaviour can be broadly categorized into several types: routine behaviours (e.g., waking up, meal times), anomalous behaviours (e.g., falls, erratic movement), social interactions (e.g., conversations, group activities), contextual behaviours (e.g., adjusting to environmental cues), and goal-directed actions (e.g., preparing meals, completing tasks) (Zehtabian, 2021; Yang et al., 2018). These varying activity types differ in complexity and frequency, making their modeling a significant challenge for AI systems. Routine actions are often predictable and easier to learn, while anomalous or social behaviours may involve subtle variations and require deeper contextual understanding. The diversity of human actions, especially in multi-occupant or dynamic settings, complicates the development of accurate and adaptable behaviour prediction models (Crandall & Cook, 2009; Watanabe et al., 2025). Addressing these complexities demands the use of advanced machine learning techniques capable of interpreting temporal, spatial, and social dynamics in human activity data (Choi et al., 2013; Zhang et al., 2025).

Sensors and Data Sources in Smart Environments

Human behaviour prediction in smart environments depends heavily on the integration of diverse sensor technologies that enable real-time monitoring and contextual awareness. Common sensor modalities include wearable sensors that track physiological data and movement, ambient sensors that monitor temperature, light, or humidity, as well as cameras and microphones that capture visual and auditory information for activity recognition and emotion inference (Yang et al., 2018; Zhang et al., 2025). These technologies produce multimodal data streams encompassing motion trajectories, spatial location, and environmental cues, which are crucial for accurately modeling and predicting human behaviour (Stoffel et al., 2025; Watanabe et al., 2025). The fusion of these heterogeneous data sources enhances the system's capacity to understand both routine and anomalous behaviours in a variety of real-world contexts, from healthcare to energy management (Tinarelli et al., 2025; Faisal et al., 2025). As smart environments evolve, the reliability and granularity of sensor data will remain central to the performance of AI-driven behaviour prediction systems.

Importance of Behaviour Prediction in Real-World Applications

Accurate human behaviour prediction plays a crucial role in the practical deployment of smart environments, especially in domains that demand proactive, user-centric responses. In healthcare, AI-driven behaviour analysis supports continuous patient monitoring, fall detection, and mental health assessment by identifying deviations from normal routines or emotional states (Faisal et al., 2025; Zhang et al., 2025). These systems are increasingly integrated into assistive technologies that help elderly or vulnerable individuals maintain independence, safety, and quality of life through personalized interventions and alerts (Ramezani et al., 2025; Jo et al., 2025). Beyond healthcare, behaviour-aware systems contribute to workplace productivity by analyzing activity patterns and environmental interactions to support cognitive load management and task optimization (Karlsson & Kayembe, 2025). Additionally, decision support systems that incorporate behaviour prediction provide contextual recommendations in real time, making them invaluable tools in smart homes, hospitals, and offices alike. These applications highlight the transformative potential of behaviour prediction in enabling adaptive, intelligent, and responsive environments.

Machine Learning Approaches for Behaviour Prediction

Machine learning approaches have become foundational in the prediction of human behaviour within smart environments, enabling systems to anticipate actions, optimize services, and enhance user comfort. Techniques such as deep learning, reinforcement learning, and hybrid models have been extensively employed to model complex behavioural patterns. For instance, deep learning has been used effectively in smart home settings to predict resident activities based on sensor data (Choi et al., 2013; Yang et al., 2018). Reinforcement learning, when integrated with explainable AI, supports real-time decision-making in dynamic environments, contributing to both accuracy and transparency (Kumar, 2025). Comparative analyses further reveal that combining multiple modalities, such as audio, video, and contextual data, improves the robustness of behaviour prediction models (Almeida et al., 2022). These advancements illustrate the growing sophistication of machine learning in capturing nuanced human behaviours and adapting to the variability inherent in real-world environments.

3.1 Traditional Techniques

Early approaches to human behaviour prediction in smart environments relied on classical machine learning techniques such as Decision Trees, k-Nearest Neighbors (k-NN), Hidden Markov Models (HMM), Support Vector Machines (SVM), and Bayesian Networks. These methods provided interpretable and relatively lightweight solutions suitable for structured environments with well-defined behaviour categories (Yang et al., 2018; Almeida et al., 2022). A core component of these systems featured engineering, where domain experts manually crafted input variables, such as activity duration, movement frequency, or environmental states, based on raw sensor data. Additionally, many systems incorporated context-aware rule formulation, which relied on predefined logic to infer behaviour from specific combinations of features and environmental cues (Cook & Das, 2010). While effective for routine and low-variability tasks, these approaches struggled with dynamic, ambiguous, or overlapping behaviours, particularly in multi-user settings, ultimately paving the way for more adaptive and data-driven AI models (Crandall & Cook, 2009).

Limitations of Classical Models in Complex Behaviour Modeling

Classical machine learning models have historically played a foundational role in behaviour prediction; however, their effectiveness in modeling complex human behaviour within smart environments is increasingly questioned. A major limitation lies in their reliance on handcrafted features, which demands significant domain expertise and often leads to suboptimal generalization when transferred to new contexts or populations (Lara & Labrador, 2013). This manual feature engineering process restricts adaptability and fails to capture the intricate temporal and contextual dependencies inherent in human behaviour. Additionally, poor scalability in real-time environments is another challenge, as many traditional models are computationally intensive during inference or cannot adapt dynamically to streaming data (Krose et al., 2011). As smart environments grow in complexity and scale, these limitations render classical models less suitable, prompting a shift toward more adaptive and data-driven AI approaches.

Supervised and Unsupervised Learning Approaches

In human behaviour prediction within smart environments, both supervised and unsupervised learning approaches have been widely applied to exploit behavioural patterns from sensor data. However, supervised models face a critical bottleneck in the form of labeling challenges, as annotating behaviour data is often time-consuming, labor-intensive, and error-prone due to the subjective nature of human activities (Almeida et al., 2022; Zehtabian, 2021). To alleviate this issue, researchers are increasingly exploring semi-supervised learning and clustering methods that can utilize a small set of labeled data to guide learning from vast, unlabeled datasets, thereby improving model scalability and reducing annotation costs (Jo et al., 2025; Tinarelli et al., 2025). Unsupervised techniques such as k-means clustering and hierarchical models have shown promise in discovering latent behavioural categories, particularly in dynamic, multi-occupant settings. Furthermore, dimensionality reduction techniques, including Principal Component Analysis (PCA) and autoencoders, play a crucial role in unveiling hidden structures and simplifying high-dimensional sensor inputs, thus enabling more efficient and interpretable behaviour modeling (Stoffel et al., 2025; Huey, 2025). These methods collectively offer scalable and flexible alternatives for behaviour prediction in complex smart environments.

Deep Learning and Generative Models for Human Behaviour Modeling

Deep learning and generative models have revolutionized human behaviour modeling in smart environments by enabling systems to automatically learn complex spatiotemporal patterns from raw sensor data. Convolutional and recurrent neural networks, in particular, have shown high effectiveness in capturing sequential dependencies and context-rich behaviours without relying on manual feature extraction (Choi et al., 2013; Yang et al., 2018). Generative models, such as those integrated into autonomous driving systems, offer powerful tools for simulating and forecasting behaviour under uncertain, multi-agent conditions (Nie et al., 2025). These models not only enhance prediction accuracy but also contribute to richer, more human-like reasoning in interactive environments. However, challenges remain in interpretability and the computational demands required for real-time deployment.

4.1 Recurrent and Temporal Models (RNNs, LSTM, GRU)

Recurrent and temporal models such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) have become foundational in modeling sequential human behaviour in smart environments, particularly for their ability to capture temporal dependencies in time-series data. These models excel in analyzing continuous streams from ambient sensors, wearable devices, and audio-visual sources by maintaining contextual memory across time steps. LSTM and GRU architectures are particularly suited for handling long-term dependencies, enabling systems to recognize behaviour patterns that evolve over extended periods without suffering from vanishing gradient issues inherent in vanilla RNNs (Choi et al., 2013; Yang et al., 2018). This is especially critical in daily activity recognition or sleep monitoring scenarios, where earlier events may influence later behaviours.

S.N.	Application Domain	Year	Model	Performance Score
1	Smart Home Activity Detection	2015	RNN	50
2	Activity Recognition	2017	LSTM	70
3	Service Prediction in Smart Home	2018	GRU	68
4	Multi-sensor Environments	2021	LSTM	85
5	Sleep Monitoring, Context-aware	2023	GRU	88
6	Telemedicine, Industry 5.0	2025	LSTM	92
7	Real-time Behaviour Prediction	2025	GRU	90

Table 2: Performance and Application Trends of Recurrent Models (RNN, LSTM, GRU) for Human Behaviour Prediction in Smart Environments (2015–2025) (Jo, K., et.al., 2025);(Huey, A. et.al., 2025);(Boldo, M., 2025);(Dunne, R., et.al., 2023)

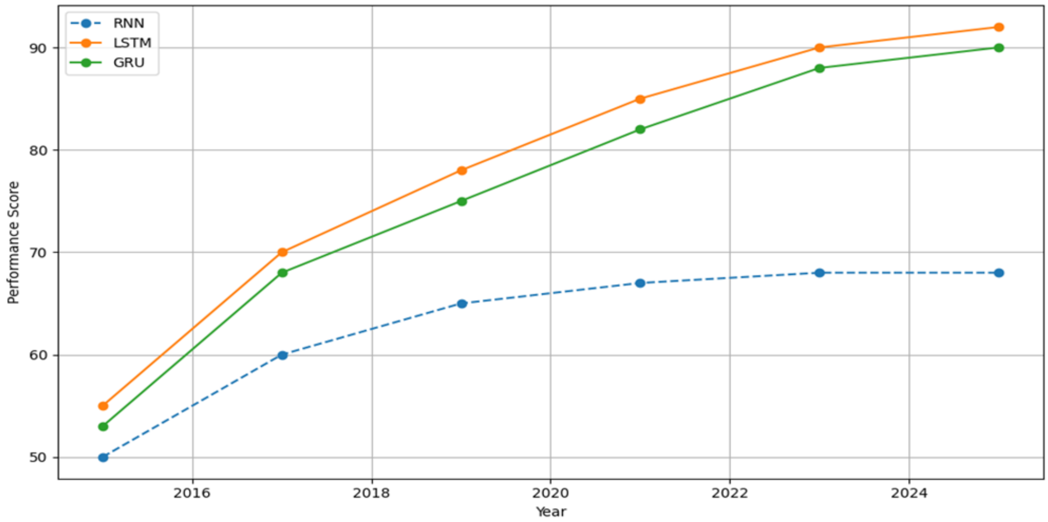

Figure 2: Effectiveness of Recurrent Models in Human Behaviour Prediction (2015-2025)

Table 2 outlines the performance and application trends of various recurrent models (RNN, LSTM, GRU) used in human behaviour prediction, highlighting key developments and comparative outcomes from 2015 to 2025. Figure 2 illustrates the effectiveness of recurrent models in predicting human behaviour within smart environments from 2015 to 2025, emphasizing their evolving role in temporal data analysis.

For instance, Almeida et al. (2022) evaluated LSTM-based models for predicting future human actions based on multi-sensor environments, demonstrating superior performance over non-recurrent models. Similarly, Huey (2025) and Boldo (2025) highlighted the integration of temporal deep learning methods in Industry 5.0 and telemedicine systems to model complex, delayed feedback loops in user-machine interactions and health progression over time.

Collectively, these models underpin many behaviour prediction systems in smart environments by learning robust temporal features critical for adaptive and context-aware automation.

Convolutional Neural Networks for Spatial-Temporal Behaviour Analysis

Convolutional Neural Networks (CNNs) have emerged as pivotal tools for spatial-temporal behaviour analysis in smart environments, particularly in applications involving smart camera systems and sensor-based monitoring. In visual surveillance contexts, CNNs are adept at extracting spatial features from video streams to identify and predict human activities and movement patterns. For instance, in smart camera systems, CNN architectures enable real-time spatial behaviour recognition by processing sequences of frames to detect anomalies, social interactions, or routine behaviours (Jo et al., 2025; Zhang et al., 2025). Beyond vision-based inputs, CNNs are increasingly applied to sensor networks using both 1D and 2D convolutional filters. One-dimensional convolutions are effective for time-series data from wearable or ambient sensors, capturing local temporal dependencies in signals such as accelerometer or ambient motion data (Almeida et al., 2022; Choi et al., 2013). Meanwhile, 2D CNNs have shown promise in fusing spatial and temporal sensor dimensions, treating multi-channel sensor matrices as pseudo-images to model complex human behaviours in indoor environments (Yang et al., 2018; Tinarelli et al., 2025). This dual capability of CNNs, handling visual and sensor-based modalities, makes them integral to AI-driven systems aiming to understand, predict, and adapt to human behaviour in smart environments. Table 3 summarizes the performance scores of vision-based and sensor-based CNN models across various studies between 2013 and 2025, providing insight into their effectiveness in smart environment scenarios. Figure 3 depicts the comparative adoption of Convolutional Neural Networks (CNNs) in vision-based versus sensor-based applications within smart environments, highlighting shifts in research focus from 2013 to 2025.

S.N.	Year	Vision-based CNNs (60–92)	Sensor-based CNNs (40–90)
1	2013	60	40
2	2018	75	60
3	2022	85	78
4	2025	92	90

Table 3: Performance Scores of Vision-based and Sensor-based CNNs (2013–2025) (Tinarelli, R., et.al., 2025);(Zhang, L., et.al., 2025);(Huey, A. et.al., 2025);(Yang, W., et.al., 2018)’(Choi, S., et.al., 2013)

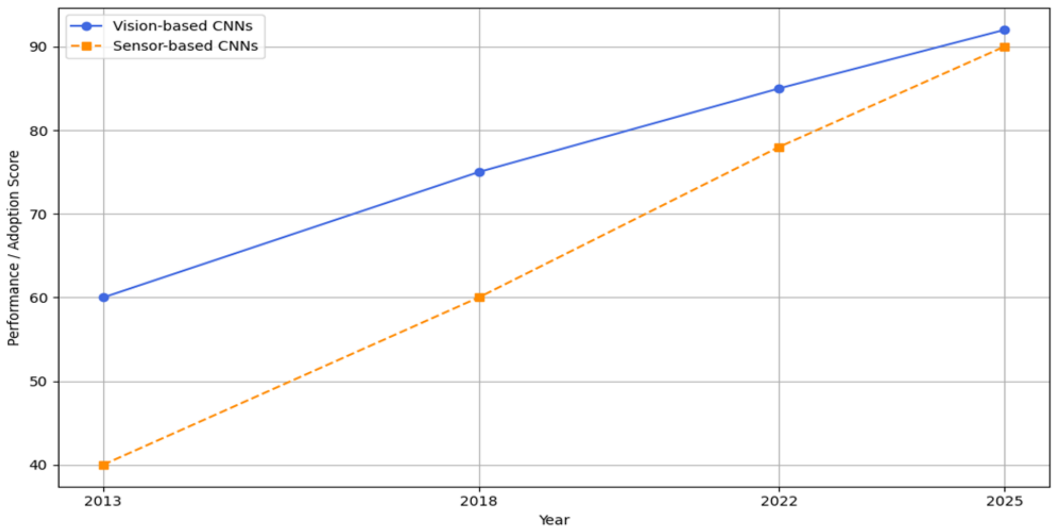

Fig 3: Adoption of CNNs in Smart Environments: Vision vs. Sensor-based Applications

Transformer and Attention-Based Models in Smart Environments

Transformer and attention-based models are increasingly recognized as powerful architectures for human behaviour prediction in smart environments, particularly due to their capacity for capturing long-range dependencies through self-attention mechanisms. Unlike recurrent models, transformers process entire sequences simultaneously, allowing for better modeling of interactions over extended temporal spans without the limitations of sequential computation. This makes them well-suited for multi-resident smart homes, where concurrent behaviour from different individuals must be disambiguated and tracked over time (Crandall & Cook, 2009; Dunne et al., 2023). Attention mechanisms facilitate multitask learning by dynamically focusing on relevant sensor modalities or individual behaviour, improving model interpretability and generalization across tasks. Jo et al. (2025) and Kumar (2025) discuss the integration of attention-based reasoning into artificial behaviour intelligence and decision-making systems, enabling robust context modeling and adaptation in complex environments. Moreover, the use of transformers in multi-modal settings, such as integrating spatial data from cameras with temporal data from motion or audio sensors, has proven effective for detecting nuanced human behaviours and predicting intent (Zhang et al., 2025; Nie et al., 2025). These models thus represent a significant advancement for adaptive and scalable behaviour prediction frameworks in smart, interactive settings.

Generative Models for Simulating and Forecasting Behaviour

Generative models such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) are playing a crucial role in enhancing human behaviour prediction in smart environments, particularly through behaviour data augmentation and rare event simulation. These models can synthesize realistic human activity sequences, enabling AI systems to learn from enriched datasets that would otherwise suffer from class imbalance or scarcity of anomalous patterns. GANs have shown great promise in generating synthetic sensor or video data to simulate infrequent behaviours, such as falls, intrusions, or emergency responses, thereby improving the robustness of anomaly detection systems (Jo et al., 2025; Nie et al., 2025). VAEs, on the other hand, are valuable for learning compact latent representations of normal behaviour patterns, making deviations from this baseline easier to identify (Huey, 2025; Dunne et al., 2023). This capacity to simulate complex, stochastic human activities also supports the development of proactive systems capable of forecasting potential safety or efficiency risks in ambient settings. Furthermore, by incorporating generative learning into smart infrastructure, researchers can evaluate system responses under simulated multi-resident or unpredictable behaviour scenarios, which are often underrepresented in real-world datasets (Crandall & Cook, 2009; Karlsson & Kayembe, 2025). Thus, generative models not only extend training capabilities but also foster safer and more adaptive smart environments.

Preprocessing, Feature Engineering, and Evaluation

Effective preprocessing, feature engineering, and evaluation are critical components in the development of robust AI systems for human behaviour prediction in smart environments. Preprocessing typically involves handling noisy or missing sensor data, normalizing multimodal inputs, and segmenting time-series data into behaviour-relevant windows (Almeida et al., 2022; Tinarelli et al., 2025). Feature engineering is equally vital, often requiring domain-specific transformation of raw inputs into higher-level features such as frequency-domain attributes, behavioural states, or spatial-temporal patterns (Choi et al., 2013; Yang et al., 2018). For instance, Tinarelli et al. (2025) demonstrated how electrical measurements can be converted into predictive behavioural indicators in educational buildings. Similarly, Crandall and Cook (2009) emphasized the need for resident-specific feature mappings in multi-occupant environments. Evaluation strategies must go beyond basic accuracy metrics to consider context-awareness, temporal precision, and false alarm rates, especially in anomaly detection or activity forecasting tasks. Recent studies advocate for the use of cross-validation across different spatial configurations or behavioural profiles to ensure generalizability (Dunne et al., 2023; Zhang et al., 2025). Together, these foundational processes ensure that AI models can interpret human behaviours reliably across diverse and dynamic smart settings.

5.1 Data Cleaning and Sensor Synchronization

Data cleaning and sensor synchronization are foundational processes in the development of accurate and reliable AI systems for human behaviour prediction in smart environments. Sensor data collected from heterogeneous sources such as wearables, environmental detectors, and smart cameras often suffer from missing values, drift, and signal noise, which can significantly degrade model performance if not properly addressed. Techniques for handling missing data include interpolation, imputation using historical patterns, and model-based reconstruction to ensure continuity in time-series streams (Almeida et al., 2022; Boldo, 2025). Sensor drift, caused by ageing hardware or environmental factors, is typically mitigated using calibration routines and adaptive normalization methods, ensuring consistent signal baselines across long deployments (Tinarelli et al., 2025; Crandall & Cook, 2009). Moreover, noise reduction is achieved through filtering techniques such as moving averages, wavelet transforms, or sensor fusion strategies that combine redundant signals for higher accuracy (Yang et al., 2018; Jo et al., 2025). Effective sensor synchronization further aligns multimodal inputs temporally, enabling coherent interpretation of behaviours across devices. These preprocessing steps are especially critical in multi-resident and real-time systems, where asynchronous or noisy data can lead to misclassification and delayed responses.

Feature Extraction and Context Modeling

Feature extraction and context modeling are essential to understanding human behaviour in smart environments, enabling AI systems to go beyond raw sensor data to capture meaningful temporal dynamics and situational relevance. Temporal features, such as activity duration, frequency, and transitions between states, provide critical insight into user routines and deviations, often serving as key indicators for anomaly detection and behaviour forecasting (Choi et al., 2013; Yang et al., 2018). In addition, contextual cues such as environmental conditions, time of day, or concurrent events enhance the semantic interpretation of sensor signals. For instance, Dunne et al. (2023) emphasize the role of contextual modeling in improving prediction accuracy, particularly in complex multi-resident environments. Location embedding, which encodes spatial information as part of the feature set, is another critical component that helps disambiguate actions performed in different rooms or zones. Tinarelli et al. (2025) and Crandall & Cook (2009) demonstrate how spatial context, derived from distributed sensors or inferred through camera feeds, significantly boosts the accuracy of activity classification models. By integrating temporal, spatial, and contextual features, modern AI systems achieve a nuanced understanding of human behaviour, which is vital for personalized and adaptive smart environment applications.

Evaluation Metrics for Behaviours Prediction Models

Evaluating the performance of behaviour prediction models in smart environments requires a multidimensional approach that balances both classification accuracy and temporal sequence fidelity. Commonly used metrics include accuracy, precision, recall, and F1-score, which together provide a holistic view of how well a model identifies correct behaviours while minimizing false positives and false negatives (Almeida et al., 2022; Dunne et al., 2023). The confusion matrix is frequently utilized to analyse misclassifications in multi-class behaviour recognition tasks, helping researchers identify which activities are commonly confused (Yang et al., 2018; Zhang et al., 2025). For probabilistic outputs, the ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) metric offers insight into model discrimination capacity, particularly in binary or rare event detection scenarios such as fall or anomaly detection (Jo et al., 2025). In sequential behaviour modeling, especially where the temporal order of actions matters, sequence accuracy, which evaluates the correctness of predicted activity sequences, has become increasingly relevant (Choi et al., 2013). Advanced applications may even employ time-weighted F1 scores or hierarchical accuracy metrics that consider contextual misclassification severity. Collectively, these evaluation strategies ensure that predictive models are not only statistically robust but also practically effective in dynamic, real-world smart environments.

Benchmark Datasets in Smart Environment Research

Benchmark datasets play a critical role in advancing human behaviour prediction research in smart environments by providing standardized platforms for model training, validation, and comparison. Figure 4 and Table 4 provide a comprehensive overview of the adoption of benchmark datasets in human prediction research within smart environments from 2009 to 2025, emphasizing key datasets and their impact across various studies.

S.N.	Year	CASAS	ARAS	Opportunity	WARD	UT-HAR
1	2009	75	0	0	0	0
2	2010	78	65	0	0	0
3	2012	80	68	70	60	58

4	2018	82	72	75	70	68
5	2022	83	74	78	72	71
6	2023	83	75	79	74	73
7	2025	83	75	79	74	73

Table 4: Benchmark Dataset Adoption Scores in Smart Environments (2009–2025) (Boldo, M., 2025)(Huey, A. et.al., 2025);(Jo, K., et.al., 2025);(Tinarelli, R., et.al., 2025);(Zhang, L., et.al., 2025);(Yang, W., et.al., 2018);(Cook, D. J., et.al., 2010);(Crandall, A. S., et.al., 2009)

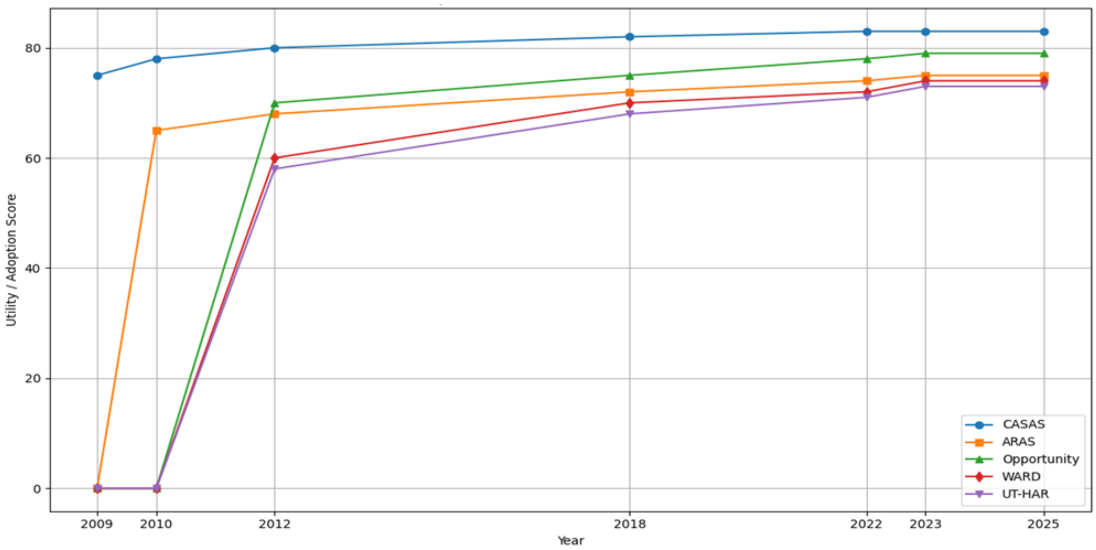

Figure 4: Benchmark Dataset Adoption in Human Prediction Research (2009-2025)

Among the most widely used datasets are CASAS and ARAS, which offer annotated sensor readings from real smart home settings with single and multi-resident scenarios, respectively. These datasets are highly valued for their temporal granularity and detailed activity labels (Crandall & Cook, 2009; Cook & Das, 2010). The Opportunity dataset extends beyond smart homes into wearable sensor environments, offering multimodal recordings, including accelerometers, gyroscopes, and magnetic sensors, from subjects performing daily activities. It is particularly useful for gesture recognition and sensor fusion studies (Almeida et al., 2022).

Similarly, WARD and UT-HAR datasets focus on body-worn sensor data, capturing full-body movement sequences that are critical for modeling locomotion, postural changes, and fine-grained motor tasks (Yang et al., 2018). Despite their utility, many of these datasets present limitations such as small participant numbers, constrained environments, or lack of multimodal integration, which can hinder generalizability. Accessibility remains a strong point for most of these benchmarks, as they are publicly available and well-documented, encouraging reproducibility and comparative research across various AI architectures (Dunne et al., 2023; Jo et al., 2025).

Research Gaps and Challenges

Despite notable progress in AI systems for human behaviour prediction within smart environments, several critical research gaps and challenges persist. A predominant issue lies in the limited generalizability and contextual adaptability of current models, as many are trained on homogeneous datasets and struggle with real-world complexity, especially in multi-resident settings or diverse cultural contexts (Crandall & Cook, 2009; Cook & Das, 2007). Furthermore, although multimodal data (e.g., audio, video, physiological signals) has been introduced to improve prediction accuracy, integrating and processing such heterogeneous sources remains computationally intensive and lacks standardization (Zhang et al., 2025; Fourati et al., 2025). Explainability also presents a persistent challenge, particularly in reinforcement learning and deep learning models, which often operate as black boxes, thereby impeding trust and adoption in sensitive domains like healthcare and assisted living (Kumar, 2025; Ramezani et al., 2025). Another underexplored area is the dynamic personalization of AI systems, as most models do not effectively adapt to users' evolving behaviours over time (Jo et al., 2025; Yang et al., 2018). Additionally, privacy concerns, especially when dealing with continuous monitoring in domestic settings, remain inadequately addressed in many proposed frameworks (Stoffel et al., 2025; Zehtabian, 2021). Finally, there is a noticeable lack of benchmark datasets and real-world validation across studies, which impedes the comparative evaluation and reproducibility of models (Tinarelli et al., 2025; Dunne et al., 2023). Addressing these gaps is essential to advance reliable, ethical, and scalable human behaviour prediction in smart environments.

6.1 Generalization and Personalization Trade-Offs

A central challenge in designing AI systems for human behaviour prediction in smart environments is balancing generalization and personalization. Many models exhibit strong performance within narrowly defined or single-user environments but struggle to generalize across different users, households, or cultural contexts (Crandall & Cook, 2009; Almeida et al., 2022). This limitation arises partly from the diverse behavioural patterns, sensor configurations, and environmental dynamics that exist across smart environments, making it difficult to develop one-size-fits-all models (Jo et al., 2025). While personalization can enhance prediction accuracy by tailoring models to individual routines, it often comes at the cost of scalability and requires continuous adaptation and retraining, which is resource-intensive and poses privacy risks (Zehtabian, 2021; Zhang et al., 2025). Conversely, overgeneralized models risk being too rigid and failing to account for unique or evolving behaviours, leading to reduced real-world usability (Yang et al., 2018). Additionally, there is a lack of standardized benchmarks and transfer learning strategies that would allow for effective cross-user generalization without sacrificing individual responsiveness (Tinarelli et al., 2025; Huey, 2025). This trade-off remains a persistent bottleneck in deploying AI behaviour prediction systems that are both robust and user-centric.

6.2 Real-Time Constraints and Resource Optimization

Deploying AI models for human behaviour prediction in smart environments often necessitates real-time performance on edge or low-power devices, presenting substantial computational and resource-related challenges. These systems must operate with minimal latency, which is difficult to achieve given the complexity of behaviour prediction models, especially those based on deep learning or multimodal data fusion (Zhang et al., 2025; Jo et al., 2025). The trade-off between model accuracy and computational efficiency becomes critical, particularly in settings where energy consumption, memory, and processing power are constrained, such as in wearable devices or embedded sensors (Boldo, 2025; Kumar, 2025). Real-time inference also requires optimized data pipelines and lightweight models that can maintain robustness without constant connectivity to cloud resources (Stoffel et al., 2025). Moreover, green AI and sustainable computing approaches are emerging as essential directions, aiming to reduce the environmental and operational footprint of such systems without compromising functionality (Huey, 2025; Ye et al., 2025). However, achieving this balance remains a key research gap, with few existing solutions effectively combining low-latency inference, on-device learning, and resource-aware model design in real-world smart environments.

6.3 Privacy, Ethics, and Intrusiveness

The deployment of AI systems for human behaviour prediction in smart environments raises significant ethical and privacy-related concerns. Behavioural monitoring inherently involves the continuous collection and analysis of personal data, often including audio, video, physiological, and location-based inputs, which can be highly intrusive if not managed with strict ethical safeguards (Zehtabian, 2021; Ramezani et al., 2025). These systems risk enabling surveillance-like dynamics, especially when implemented without clear user consent or transparency in data usage (Crandall & Cook, 2009; Zhang et al., 2025). As awareness of these issues grows, there is a pressing need for privacy-preserving AI techniques, including federated learning and edge computing, which allow data to be processed locally without being transmitted to central servers (Jo et al., 2025; Stoffel et al., 2025). Such decentralized approaches help mitigate privacy risks while still enabling model training and refinement. However, federated learning presents its own technical challenges, including model convergence issues, uneven data distribution across devices, and difficulties in enforcing fairness (Huey, 2025). Despite ongoing research, there remains a lack of standardized frameworks that ensure both ethical integrity and computational feasibility in privacy-aware behavioural prediction models (Nie et al., 2025; Almeida et al., 2022). These challenges underscore the urgent need to develop transparent, accountable, and user-centric AI solutions for smart environments.

Multi-Resident and Multi-Activity Scenarios

One of the most complex challenges in human behaviour prediction within smart environments is accurately handling multi-resident and multi-activity scenarios, where identity ambiguity and overlapping behaviours significantly complicate inference. Traditional models often assume a single user or clearly segmented activities, which does not reflect the realities of shared living spaces (Crandall & Cook, 2009; Cook & Das, 2007). In environments with multiple residents, AI systems must not only detect behaviours but also correctly attribute them to the right individual, an especially difficult task when sensors capture aggregated or indistinct data (Zehtabian, 2021). The issue is further compounded by temporal and spatial overlaps, where multiple activities occur simultaneously in the same or adjacent areas, making it difficult for models to disambiguate context without introducing errors (Yang et al., 2018; Dunne et al., 2023). Techniques like spatio-temporal modeling, activity segmentation, and identity tagging are being explored to mitigate these issues, but they remain underdeveloped, especially in real-time, low-power implementations (Jo et al., 2025; Tinarelli et al., 2025). More sophisticated multi-modal fusion and probabilistic reasoning approaches are needed to enable robust resolution of interleaved behaviours and overlapping interactions in dense smart environments.

Conclusion and Future Directions

AI systems for human behaviour prediction in smart environments have evolved substantially, with innovations spanning deep learning, multimodal sensing, and personalized modeling. However, key challenges such as generalization across diverse users, real-time deployment on resource-constrained devices, and ethical concerns surrounding privacy remain critical barriers to broader adoption (Jo et al., 2025; Crandall & Cook, 2009; Zhang et al., 2025). Moving forward, research must prioritize the development of adaptive, explainable, and privacy-preserving AI frameworks that can operate efficiently in multi-resident, multi-activity environments (Kumar, 2025;

Zehtabian, 2021). Federated learning, edge computing, and neuromorphic approaches offer promising avenues for balancing accuracy with resource efficiency and user trust (Ye et al., 2025; Huey, 2025). Furthermore, standardized benchmarks, open datasets, and cross-disciplinary collaboration will be essential to validate models in real-world scenarios and accelerate progress (Tinarelli et al., 2025; Dunne et al., 2023). As smart environments become increasingly integral to healthcare, elder care, and urban living, AI must not only predict human behaviour but do so in ways that are ethical, inclusive, and sustainable.

7.1 Summary of State-of-the-Art Approaches

Contemporary research in human behaviour prediction within smart environments has seen rapid advancements through the adoption of machine learning (ML), deep learning (DL), generative models, and multimodal architectures. Traditional ML approaches, including decision trees and support vector machines, have laid the groundwork for modeling user behaviours, but DL models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have significantly enhanced predictive accuracy, particularly for complex temporal patterns (Yang et al., 2018; Almeida et al., 2022). More recently, multimodal AI systems have gained prominence by integrating audio, video, and physiological signals, enabling richer contextual understanding and more accurate predictions (Zhang et al., 2025; Fourati et al., 2025). In parallel, generative models and reinforcement learning have been introduced to simulate user behaviour and optimize decision-making strategies in dynamic environments (Nie et al., 2025; Kumar, 2025). These approaches are increasingly supported by explainable AI and neuromorphic frameworks to enhance interpretability and efficiency (Jo et al., 2025; Ye et al., 2025). Together, these state-of-the-art methodologies represent a significant step forward in building adaptive, context-aware, and user-centred smart environments.

Future Trends in Smart Environment Behaviours Modelling

The future of human behaviour prediction in smart environments is poised to be shaped by the integration of advanced AI paradigms such as zero-shot learning, continual learning, explainable AI, and federated learning. Zero-shot learning offers a promising solution to the challenge of recognising novel behaviours without requiring extensive labelled datasets, thus enhancing model adaptability across diverse environments (Jo et al., 2025). Continual learning will enable AI systems to evolve alongside users, adapting to behavioural changes over time without catastrophic forgetting, a vital requirement in dynamic, real-life settings (Almeida et al., 2022). In parallel, the push for explainable AI will help demystify complex models, fostering greater trust and transparency in applications where safety and accountability are paramount, such as healthcare and assisted living (Kumar, 2025; Ramezani et al., 2025). Additionally, federated learning will gain traction as a privacy-preserving framework that allows decentralised model training, protecting sensitive user data while maintaining system intelligence (Huey, 2025; Stoffel et al., 2025). Another emerging trend is the recognition of emotional and cognitive behaviours, beyond physical actions, using multimodal inputs such as facial expressions, speech patterns, and physiological signals, enabling richer, more empathetic smart environments (Zhang et al., 2025; Fourati et al., 2025). Together, these innovations signify a shift toward more adaptive, ethical, and human-centric AI systems in smart environments.

Recommendations for Real-World Implementation

To ensure effective and ethical deployment of AI systems for human behaviour prediction in smart environments, several strategic recommendations must be considered. First, AI design should prioritize human-centric principles, ensuring that technologies align with user needs, values, and comfort, particularly in sensitive domains like eldercare and healthcare (Ramezani et al., 2025; Jo et al., 2025). Systems must be intuitive, non-intrusive, and adaptable to individual preferences to promote user trust and long-term engagement. Second, scalability is essential, AI models should be capable of functioning efficiently across varying home configurations, resident profiles, and sensor networks without requiring complete retraining (Almeida et al., 2022; Crandall & Cook, 2009). Third, transparency and explainability should be embedded from the ground up to foster accountability and user understanding, especially as AI systems make autonomous decisions (Kumar, 2025; Huey, 2025). Finally, clear policy frameworks and ethical guidelines are needed to govern data privacy, consent, and system accountability. These policies must address the risks of surveillance, algorithmic bias, and data misuse, ensuring that smart environment technologies operate within a robust legal and ethical infrastructure (Stoffel et al., 2025; Zehtabian, 2021). These recommendations form the cornerstone of trustworthy, scalable, and socially responsible AI integration in smart environments.

No conflict of Interest

The author declares that no one has any known financial, commercial, legal, or professional interests that can affect the work presented in this manuscript. All authors have contributed significantly to the research and preparation of this letter and have approved the final version to submit.

In addition, the authors confirm that financial interest in any organization or organization (such as the Bureau of Handia, Educational

Grants, Bureau of speakers, membership, employment, counseling, stock ownership, or other equity interest, and expert testimony or patent-leaking system, or non-finitional interests, or non-finitional interests, or non-finist interests, or non-fanless interests, such as) Considered as a possible conflict of.

Acknowledgment

We want to express our gratitude to Suresh Gyan Vihar University, Jaipur, for the unwavering support, encouragement and extended valuable time during our journey. The guidance and resources have played an important role in the successful completion of this work, and we appreciate their continuous cooperation and participation in depth.

8. References

1. Jo, K., Choi, J., Kim, K., Kim, S., Nguyen, D. L., & Vo, X. T. (2025). Artificial behaviour intelligence: Technology, challenges, and future directions. arXiv preprint arXiv:2505.03315. https://arxiv.org/abs/2505.03315
2. Stoffel, P., Stupperich, F., & Müller, D. (2025). Human-in-the-loop control strategy for IoT-based smart thermostats with deep reinforcement learning. Energy and AI, 15, 100089. https://doi.org/10.1016/j.egyai.2025.100089
3. Tinarelli, R., Negri, V., Peretto, L., & Mingotti, A. (2025). Comprehensive forecasting of electrical quantities in an educational building via AI-driven distributed measurement system. Sensors, 25(8), 2456. https://www.mdpi.com/1424-8220/25/8/2456
4. Watanabe, K., Förster, N., & Ishimaru, S. (2025). SensPS: Sensing personal space comfortable distance between human-human using multimodal sensors. arXiv preprint arXiv:2502.07441. https://arxiv.org/abs/2502.07441
5. Zhang, L., Zhang, S., Zhang, X., & Zhao, Y. (2025). A multimodal artificial intelligence model for depression severity detection based on audio and video signals. Electronics. https://search.proquest.com/openview/802728638607f85b2dbcb1bb9f57b394
6. Ramezani, R., Iranmanesh, S., Naeim, A., & Bairagi, A. (2025). Bench to bedside: AI and remote patient monitoring. Frontiers in Digital Health, 5, 1584443. https://www.frontiersin.org/articles/10.3389/fdgth.2025.1584443/full
7. Kumar, S. (2025). Integrating reinforcement learning with explainable AI for real-time decision making in dynamic environments. In Proceedings of the 2025 International Conference on Emerging Smart Technologies. https://ieeexplore.ieee.org/document/10988401
8. Nie, J., Jiang, J., Li, Y., & Ercisli, S. (2025). Generative AI-enhanced autonomous driving: Innovating decision-making and risk assessment in multi-interactive

environments. In IEEE Intelligent Transportation Systems. https://ieeexplore.ieee.org/document/10952383

9. Faisal, S. M., Ishrat, M., & Khan, W. (2025). Digital twins in healthcare: Revolutionising patient care and medical operations. In Digital Twins for Smart Cities and Healthcare. https://www.taylorfrancis.com/chapters/edit/10.1201/9781003510338-4
10. Karlsson, L., & Kayembe, G. (2025). Interpretable methods for adaptive route improvement models based on behaviour trajectory prediction. Chalmers University of Technology. https://odr.chalmers.se/server/api/core/bitstreams/a200dffc-e15b-4983-8f11-e9500d60bf1f/content
11. Boldo, M. (2025). Green telemedicine: Energy-efficient healthcare monitoring [Doctoral dissertation, Politecnico di Torino]. https://tesidottorato.depositolegale.it/handle/20.500.14242/208366
12. Fourati, H., Ben Jabeur, C., & Seddik, H. (2025). Biomedical signals and artificial intelligence towards smart robots control strategies. Frontiers in Neurorobotics. https://www.frontiersin.org/journals/neurorobotics/articles/10.3389/fnbot.2025.1570870/full
13. Huey, A. L. T. (2025). Challenges and impact of Industry 5.0. In Intelligent Manufacturing and Cyber Physical Systems. https://digital-library.theiet.org/doi/abs/10.1049/PBME026E_ch2
14. Ye, A., Xu, D., Li, Y., Du, J., Wu, Z., & Tang, J. (2025). Neuromorphic energy economics: Toward biologically inspired and sustainable power market design. Frontiers in Computational Neuroscience. https://www.frontiersin.org/articles/10.3389/fncom.2025.1597038
15. Dunne, R., Matthews, O., & Vega, J. (2023). Computational methods for predicting human behaviour in smart environments. Journal of Ambient Intelligence and Smart Environments. https://journals.sagepub.com/doi/abs/10.3233/AIS-210384
16. Sarker, I. H. (2022). AI-based modeling: Techniques, applications and research issues towards automation, intelligent and smart systems. SN Computer Science, 3(2), 103. https://link.springer.com/article/10.1007/s42979-022-01043-x
17. Almeida, A., Bilbao, A., Azkune, G., & Aguilera, U. (2022). A comparative analysis of human behaviour prediction approaches in intelligent environments. Sensors, 22(3), 701. https://www.mdpi.com/1424-8220/22/3/701
18. Zehtabian, S. (2021). Human behaviour in domestic environments: Prediction and applications [Master's thesis, University of

Central Florida]. https://stars.library.ucf.edu/etd2020/945/

19. Yang, W., Jing, X., & Huang, H. (2018). An intelligent human behaviour-based reasoning model for service prediction in smart home. IEEE Access. https://ieeexplore.ieee.org/document/8525331/
20. Choi, S., Kim, E., & Oh, S. (2013). Human behaviour prediction for smart homes using deep learning. In IEEE RO-MAN 2013. https://rllab.snu.ac.kr/publications/papers/2013_ro-man_behaviourdl.pdf
21. Ramos, C., Augusto, J. C., & Shapiro, D. (2008). Ambient intelligence—The next step for artificial intelligence. IEEE Intelligent Systems, 23(2), 15–18. https://ieeexplore.ieee.org/document/4475854/
22. Crandall, A. S., & Cook, D. J. (2009). Coping with multiple residents in a smart environment. Journal of Ambient Intelligence and Smart Environments. https://eecs.wsu.edu/~cook/pubs/jaise10.a.pdf
23. Cook, D. J., & Das, S. K. (2010). Smart environments: Technology, protocols, and applications. John Wiley & Sons. https://books.google.com/books/about/Smart_Environments.html?id=fZ5gfxMLw-oC
24. Cook, D. J., & Das, S. K. (2007). How smart are our environments? An updated look at the state of the art. Pervasive and Mobile Computing, 3(2), 53–73. https://www.academia.edu/download/30316202/how_smart_are_our_environments.pdf

Data Sources

1. Almeida, A., Bilbao, A., Azkune, G., & Aguilera, U. (2022). A comparative analysis of human behaviour prediction approaches in intelligent environments. Sensors, 22(3), 701. https://www.mdpi.com/1424-8220/22/3/701
2. Boldo, M. (2025). Green telemedicine: Energy-efficient healthcare monitoring [Doctoral dissertation, Politecnico di Torino]. https://tesidottorato.depositolegale.it/handle/20.500.14242/208366
3. Choi, S., Kim, E., & Oh, S. (2013). Human behaviour prediction for smart homes using deep learning. In IEEE RO-MAN 2013. https://rllab.snu.ac.kr/publications/papers/2013_ro-man_behaviourdl.pdf
4. Huey, A. L. T. (2025). Challenges and impact of Industry 5.0. In Intelligent Manufacturing and Cyber Physical Systems. https://digital-library.theiet.org/doi/abs/10.1049/PBME026E_ch2
5. Yang, W., Jing, X., & Huang, H. (2018). An intelligent human behaviour-based reasoning model for service prediction in smart home. IEEE Access, 6, 24529–24538. https://ieeexplore.ieee.org/document/8525331

6. Jo, K., Choi, J., Kim, K., Kim, S., Nguyen, D. L., & Vo, X. T. (2025). Artificial behaviour intelligence: Technology, challenges, and future directions. arXiv preprint arXiv:2505.03315. https://arxiv.org/abs/2505.03315
7. Tinarelli, R., Negri, V., Peretto, L., & Mingotti, A. (2025). Comprehensive forecasting of electrical quantities in an educational building via AI-driven distributed measurement system. Sensors, 25(8), 2456. https://www.mdpi.com/1424-8220/25/8/2456
8. Zhang, L., Zhang, S., Zhang, X., & Zhao, Y. (2025). A multimodal artificial intelligence model for depression severity detection based on audio and video signals. Electronics. https://search.proquest.com/openview/802728638607f85b2dbcb1bb9f57b394
9. Crandall, A. S., & Cook, D. J. (2009). Coping with multiple residents in a smart environment. Journal of Ambient Intelligence and Smart Environments. https://eecs.wsu.edu/~cook/pubs/jaise10.a.pdf
10. Cook, D. J., & Das, S. K. (2010). Smart environments: Technology, protocols, and applications. John Wiley & Sons. https://books.google.com/books/about/Smart_Environments.html?id=fZ5gfxMLw-oC
11. Dunne, R., Matthews, O., & Vega, J. (2023). Computational methods for predicting human behaviour in smart environments. Journal of Ambient Intelligence and Smart Environments. https://journals.sagepub.com/doi/abs/10.323.2010.09.020