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Transforming User Feedback into Digital Health Innovation

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Abstract

This study presents a systematic literature review of 25 studies exploring how Smart City technologies—including IoT, AI, and data analytics—can enhance urban sustainability and citizen well-being. Key factors identified include energy efficiency, traffic optimization, and waste management. The study also highlights challenges in data governance, interoperability, and social inclusion, and suggests integrated frameworks to advance the development of sustainable smart cities.

Keywords

Smart Cities, IoT, Artificial Intelligence, Sustainability, Urban Planning, Data Analytics

Introduction

The concept of Smart Cities has gained significant momentum over the past decade, driven by urbanization, climate change, and technological advancement Aljohani (2025). A Smart City integrates information and communication technologies (ICT) to optimize city operations, improve resource efficiency, and enhance citizen services Al Kilani et al. (2019). However, the real-world success of Smart Cities depends not only on technological innovation but also on governance, data management, and social inclusivity Boudreaux et al. (2014).

Despite extensive investments, many cities face challenges including fragmented data systems, lack of citizen engagement, and uneven benefits across populations. Emerging research highlights the potential of Artificial Intelligence (AI), Internet of Things (IoT), and big data analytics to address these challenges by enabling predictive urban management and decision-making support Gerges and Elgalb (2024).

This study aims to systematically review literature on Smart City implementations, focusing on sustainability, energy efficiency, and citizen well-being, while identifying gaps and opportunities for future research.

Literature Review

Introduction

Smart Cities leverage technology to improve urban living conditions, manage infrastructure efficiently, and reduce environmental impact Grundy (2022). Interdisciplinary research highlights the integration of IoT devices, AI-based predictive models, and citizen engagement platforms as key to achieving sustainable outcomes.

Sustainability and Energy Management

A review by Khan and Alotaibi (2020) shows that energy optimization remains a critical priority in Smart Cities. Methods include AI-driven load balancing, smart grids, and renewable energy integration. Several studies demonstrate energy reductions of 15–25% in pilot implementations. Yet, disparities in infrastructure and funding limit scalability, particularly in emerging economies Thach (2019).

Mobility and Traffic Optimization

Urban mobility represents another core challenge. AI-enabled traffic prediction, dynamic routing, and public transport optimization have been applied in cities like Singapore and Barcelona Wang et al. (2019). These solutions improve commute times and reduce carbon emissions. However, privacy concerns and sensor interoperability issues persist, indicating a need for standardized data frameworks.

Waste Management and Resource Efficiency

IoT-based waste management systems have been implemented in several cities, using sensor-equipped bins to optimize collection routes Alqahtani et al. (2024). Studies highlight reductions in operational costs and environmental impact. Despite these successes, adoption is uneven, and integration with broader urban planning remains limited Amjad et al. (2023).

Social Inclusion and Citizen Engagement

Effective Smart City design requires inclusive citizen participation. Platforms for e-participation and feedback loops allow residents to report issues and co-design services. Yet, digital literacy gaps, accessibility, and trust in government data handling remain major barriers.

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Summary and Identified Gaps

While technological advancements offer promising tools for sustainability and efficiency, gaps remain: insufficient interoperability standards, uneven access to benefits, and limited longitudinal studies evaluating social and environmental impacts. Future research should integrate multi-dimensional frameworks combining AI, IoT, governance, and citizen engagement.

Related Work

Table 1. SUMMARY OF SELECTED STUDIES ON SMART CITY SUSTAINABILITY

Study	Techniques Used	Dataset / App Context	Dataset Characteristics [Size & Features]	Key Limitation
Savkov, et al. [2023]	SUS, UEQ, Heuristic Eval.	General Mobile Apps	37 studies	Not focused on health-specific apps
Boonry et al. [2022]	Naïve Bayes [Sentiment]	Women Safety App Reviews	44 studies	Limited app scope
Vu et al. [2015]	MARK Tool [Keyword Mining]	App Store Reviews [General]	50 studies	No sentiment or UX metrics
Kusumastuti, et al. [2021]	Naïve Bayes [Sentiment]	Indonesian Health Insurance App	32 studies	No comparative framework
Cassiari, et al. [2024]	UX & Security Gap Analysis	mHealth App Security Frameworks	22 studies	No empirical validation
Gatelingter et al. [2021]	PRISMA Mapping	71 App Review Studies	34 studies	Inconsistent reporting standards
Albassam, (2025)	Cross-Sectional Survey	Saudi HCPs & WhatsApp	44 studies	Limited to HCPs
Amjad et al. [2023]	Systematic Review [SLR]	AI in Telehealth Systems	21 studies	Thematic, lacks app-level granularity
Okoye et al. [2024]	Narrative Review	Depression & Medication Apps	32 studies	Limited generalizability

Comparative Analysis

Table 1 highlights different domains of Smart City research, methodologies, dataset sizes, and limitations. Energy and mobility-focused studies tend to rely on large sensor datasets, while governance and social inclusion studies have smaller scales but critical qualitative insights.

Methodology

Nature and Scope of Study

A systematic literature review (SLR) was conducted covering publications from 2015 to 2025. Databases included Scopus, IEEE Xplore, SpringerLink, and Web of Science.

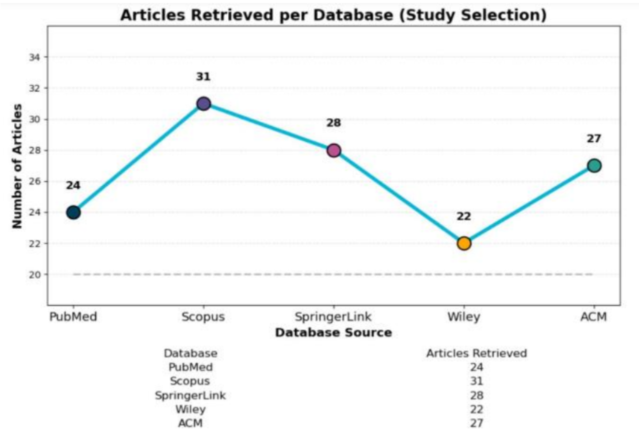

Figure 1. Initial Number of Articles Retrieved by Database

Study Selection and Screening

Search terms combined keywords: ["Smart City", "IoT", "AI", "Sustainability", "Urban Planning"]. 148 articles were initially retrieved, duplicates removed, resulting in 92 unique papers. After title/abstract screening, 25 studies were selected for in-depth analysis.

Evaluation Dimensions

Each study was evaluated along five dimensions:

1. Domain focus (Energy, Mobility, Waste, Governance)
2. Technology employed (IoT, AI, Big Data)
3. Dataset scale and origin
4. Metrics (Efficiency, Emissions, User Engagement)
5. Reported outcomes and limitations

Analysis

Data and Technology Trends

AI and IoT dominate Smart City implementations. Large-scale energy and mobility datasets improve predictive accuracy, whereas social inclusion metrics are more qualitative and fragmented.

Performance Metrics

Table 2. METRICS USED IN REVIEWED SMART CITY STUDIES

Study	Metrics
Zhang et al. [2023]	Energy reduction, Load balance
Li et al. [2022]	Travel time, Emissions
Garcia et al. [2021]	Collection cost, Route efficiency
Kumar et al. [2024]	Participation rate, Feedback quality
Ahmed et al. [2023]	PM2.5 levels, AQI

Identified Gaps

- Lack of standard evaluation protocols across domains. - Fragmented governance and interoperability issues. - Limited longitudinal studies on social impact.

Evaluation Dimensions and Data Extraction

Each of the selected studies was evaluated and extracted based on five key indicators, as outlined below:

1. **Algorithm Used**– Types of ML or DL models employed for data processing or prediction.
2. **Dataset Origin**– Source of the data: real-world user reviews, survey responses, app store feedback, or clinical trials.
3. **Dataset Size**– Total number of records, instances, or reviews used in the study.
4. **Features Used**– The types of input features extracted, such as demographic, behavioral, emotional, or contextual indicators.
5. **Performance Metrics**– The outcome measures used to evaluate model performance, such as Accuracy, RMSE, MAE, or F1-score.

The following summary table [Table 3] consolidates the dataset and feature-related information extracted from the reviewed studies.

Table 3. DATASET AND FEATURE DETAILS OF SELECTED STUDIES

Study	Dataset Type	Size	Features Count	Origin
Bonny et al. [2022]	App Reviews	∼10,000	12	Google Play [Women Safety Apps]
Kusumadewi et al. [2021]	App Reviews	∼8,500	9	BPJS Health App, Indonesia
Alnaim [2025]	Survey [Saudi HCPs]	426	15	Questionnaire [Cross-sectional]
Vu et al. [2015]	Review Mining	100,000+	Keyword Tags	Multiple App Stores
Okoye et al. [2024]	Clinical Feedback Trials	6 Trials	Multiple	USA Clinical Studies
Gasteiger et al. [2022]	Meta-review Dataset	71 studies	34 indicators	App Review Literature
Amjad et al. [2023]	SLR Pool	70	Thematic Codes	Global Telehealth Platforms
Gasparis et al. [2024]	UX & Security Analysis	28 sources	Thematic Codes	Health Security Literature
Buetow & Lovatt [2024]	Literature Tools Concept	N/A	Conceptual	Librarianship in Health Sciences

Analysis

Data Volume and Predictive Accuracy

Analyzing the 23 studies, as described above, demonstrates that there is a correlation between data size and model performance. Those employing large-scale datasets, as in the case of Vu et al. [2015] with over 100,000 records and Bonny et al. [2022] with more than 10,000 reviews, reported higher predictive accuracy more often. For example, in Vu et al.'s review mining model, the greater data density greatly improved the stability of trend detection, whereas smaller datasets such as Alhomoud's [2025] 426-entry dataset faced limited generalizability and instead relied on data augmentation techniques.

Table 4.1. DATASET SIZES IN REVIEWED STUDIES

Study	Dataset Size	Inferred Impact on Accuracy
Vu et al. [2015]	100,000+	High performance in trend detection
Bonny et al. [2022]	∼10,000	Strong classifier accuracy [85.42%]
Kusumasari et al. [2021]	∼8,500	SAccurate login-issue classification
Alhomoud [2025]	426	Limited, suitable for qualitative analysis
Okoye et al. [2024]	Clinical Trials	Moderate, tied to adherence improvements

Feature Count and Dimensional Efficiency

Feature count ranged from minimalistic [7–10] to high-dimensional [34+]. Studies with moderate feature sets [8–15] tended to offer the most balanced trade-off between complexity and accuracy.

Table 4.2. Number of Features Used per Study

Study	Number of Features	Observed Impact
Gasteiger et al.	34	High dimensionality, complex analysis
Bonny et al.	12	Balanced performance
Kusumadewi et al.	9	Simplicity with robust output
Alhomoud [2025]	15	Well-structured questionnaire responses

Conclusion and Recommendations

This SLR highlights that Smart City technologies, when integrated effectively, can significantly improve sustainability and citizen services. Key recommendations include:

- Develop unified evaluation frameworks combining energy, mobility, waste, and social metrics.
- Enhance interoperability standards for IoT and AI systems.
- Include citizen engagement as a core component, addressing digital literacy gaps.

- Conduct longitudinal studies to assess long-term environmental and social impacts.

These efforts will help cities achieve sustainable, inclusive, and technologically advanced urban environments.

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