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# An AI-Based Evaluation Framework for Smart Building Integration into Smart City

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**Abstract:** The integration of smart buildings (SBs) into smart cities (SCs) is critical to urban development, with the potential to improve SCs' performance. Artificial intelligence (AI) applications have emerged as a promising tool to enhance SB and SC development. The authors apply an AI-based methodology, particularly Large Language Models of OpenAI ChatGPT-3 and Google Bard as AI experts, to uniquely evaluate 26 criteria that represent SB services across five SC infrastructure domains (energy, mobility, water, waste management, and security), emphasizing their contributions to the integration of SB into SC and quantifying their impact on the efficiency, resilience, and environmental sustainability of SC. The framework was then validated through two rounds of the Delphi method, leveraging human expert knowledge and an iterative consensus-building process. The framework's efficiency in analyzing complicated information and generating important insights is demonstrated via five case studies. These findings contribute to a deeper understanding of the effects of SB services on SC infrastructure domains, highlighting the intricate nature of SC, as well as revealing areas that require further integration to realize the SC performance objectives.

**Keywords:** smart building; smart city; evaluation framework; artificial intelligence; OpenAI ChatGPT-3; Google Bard



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## 1. Introduction

The fast development of artificial intelligence (AI) has provided buildings and cities with the ability to become smart and the power to learn. The concept of the smart city has a complex relation to the ongoing progress and evolution of technology [1–3]. The Internet of Things (IoT) has greatly improved the digital infrastructure of cities, making it one of the most often-utilized forms of information and communication technology (ICT) [4]. The city's system consists of two primary components: infrastructure and services. The infrastructure layer includes physical components like roads, buildings, and utilities that form the foundation of the urban system. On top of that, the services layer, also known as the application layer, acts as the interface between the city system and its citizens [5,6]. The integration of modern technologies like IoT, AI, digital twins, and cloud computing has the potential to revolutionize every aspect of a traditional city, allowing objects to function autonomously without significant dependence on external support [7–9]. The primary idea behind smart cities is the employment of information and communication technology within the pre-existing infrastructure of a city [7,10,11].

Smart buildings and smart cities are very intricate, with a variety of diverse technologies and systems operating in harmony [12–14]. SB evaluation methods include frameworks to evaluate building smartness based on the Smart Readiness Indicator (SRI) [15] and SPIRE [16]. In 2018, the European Commission introduced the SRI framework to assess buildings for smart technology readiness, including building systems integration, real-time data, and human-centered design. UL Solutions, a global leader in applied safety research, created the SPIRE certification program to promote SB sustainability, performance, innovation, dependability, and user-friendliness. Since SBs incorporate sustainable construction practices, BREEAM, LEED, DGNB, and other national frameworks guide sustainable building design, construction, and assessment. The European Commission recently launched LEVEL(s), a sustainable building framework that relates construction performance to policy goals [17–20].

Several SC assessment frameworks including Urban Metabolism (UM) by Derrible et al. [21], the European Green Capital Award [22], the Sustainable Cities Index [23], urban sustainability indicators by Mega and Pedersen, 1998 [24], and the Smart City Index (SCI) [25]. Reference Framework for Sustainable Cities (RFSC) [26], United for Smart Sustainable Cities (U4SSC) [27], and Cities in Motion Index (CIMI) [28] are essential in assessing and enhancing the quality of life, environmental effects, and resource management in urban areas. By emphasizing social welfare, economic efficiency, and environmental excellence, these models aim to provide far-reaching measures to help stakeholders understand and improve resilience and urban sustainability.

Mega and Pedersen [24] suggested urban sustainability metrics that offer a whole range of assessments for city performance. The European Green Capital Award recognizes cities that have made significant advancements in improving the surroundings and supporting creative municipal sustainability projects. Offering a whole picture of urban sustainability to guide policy-making, the Sustainable Cities Index evaluates cities depending on social, environmental, and financial criteria. Derrible et al. [21] defined Urban Metabolism (UM) as a technique for tracking and evaluating material and energy movement throughout metropolitan areas. Its goal is to find inefficiencies and enhance approaches to sustainability.

Still, these models have some notable limitations: difficulties establishing standardization, data access, data management of complexity, and data correctness. One must constantly improve the data infrastructure and assessment processes if one is to overcome these challenges. Dealing with these constraints will help to maximize the effectiveness of these systems in promoting sustainable urban development and improving the quality of life for city people.

However, there are only a few studies analyzing the interconnection of SB and SC performance. Existing frameworks like [29–32] evaluate technical and non-technical aspects of SB integration into the SC system, but they face challenges in handling dynamic urban situations and fast-changing technology. They also struggle to reflect complicated relationships between SBs and urban systems, and find it challenging to assess long-term intelligence and efficacy. More comprehensive methods that can evaluate building characteristics, environmental sustainability and new technology while enhancing interoperability between particular smart projects and larger metropolitan networks are needed. It is increasingly acknowledged that the evaluation of SBs should not be done in isolation, but rather in terms of their integration with broader smart city systems and goals [33,34]. The integration of SBs into smart cities poses a multitude of challenges that require thorough and adaptable evaluation methodologies [35,36]. It has been noted that a significant challenge is the absence of standardized assessment frameworks [37].

Lately, numerous applications, including chatbot development, language translation, computer vision, sentiment analysis, voice recognition, and text summarization, have made use of Natural Language Processing (NLP), allowing computers to understand, interpret, and generate human language [38]. Large language models (LLMs) have revolutionized the domain of NLP, as they have significantly increased the capacity of computers to accurately and efficiently comprehend and generate human language [39]. This includes emerging applications from question-answering systems to language translation [39,40]. Deep learning (DL) techniques are used by large language models to improve the effectiveness of conventional NLP tasks such as sentiment and contextual analysis. This was accomplished by increasing the number of training datasets and leveraging sophisticated computer capabilities. This illustrates the ongoing attempt to attain and surpass the level of proficiency that humans possess in understanding and articulating language [41,42]. However, there is a lack of studies on the use of deep learning and NLP in the context of SB. This is apparent from the scarcity of research undertaken by [43,44]. The scientific literature has not investigated how sophisticated AI applications may be used to evaluate SBs' impact on smart city performance. DL algorithms in LLMs offer a more complete and accurate assessment of the variables influencing complex and multidimensional systems than traditional approaches, even though NLP is capable of handling enormous volumes of linguistic data from several sources [45–47].

The primary aim of this research is to develop and validate a comprehensive methodology for evaluating how well SB services are integrated into the larger SC ecosystem and infrastructure. The framework's specific objective is to assess how different SB components affect the performance of SCs in terms of three important areas: resilience, efficiency, and environmental sustainability. Additionally, it aims to ascertain the relative significance and order of precedence of several SC infrastructure sectors (energy, transportation, water, waste, and security) to facilitate the efficient integration of SBs. Large language models (LLMs) like Google's Bard and OpenAI's ChatGPT-3 are used in the study as expert evaluators to analyze the intricate relationships and interdependencies between SC infrastructure and SB services in order to accomplish this goal. Thus, this study advances the field by moving beyond the siloed treatment of SBs and SCs. It proposes a framework not only for bridging the links between the two complex systems but also innovative tools for assessing their integration. This approach is expected to promote a more resilient, efficient and sustainable urban environment, and ultimately contribute to the broader objectives of smart urban development.

The layout of the paper is as follows: Firstly, a review of the recent SBs and smart city research, followed by existing assessment frameworks, related to the integration of SB into SC is presented, and the applications of advanced artificial intelligence including NLP and LLMs for SBs and smart cities are analyzed. To accomplish the study objective, the detailed methodology is elaborated, encompassing the theoretical framework and suggested evaluation techniques, with a particular focus on leveraging the expertise of OpenAI ChatGPT-3 and Google Bard as AI specialists, as well as framework validation. Next, analyses and a discussion of the results of utilizing the suggested framework in five demonstration cases follow. Ultimately, the study culminates with conclusions and prospects for further investigations.

## 2. Literature Review

### *2.1. Smart Buildings and Smart Cities*

SBs play a crucial role in the efficient performance of SCs [5,30,31,48]. They have the potential to bring about positive changes such as resilience, sustainability, connectedness, and smart environments for people all over the world. This global shift towards smarter buildings is a significant step forward [48,49]. SB uses cutting-edge digital technologies, algorithms and analytics to provide substantial benefits to tenants, building owners and operators. These cutting-edge technology applications can be divided into six groups: energy, mobility, well-being, security, water, and waste management [29,50]. In the various phases of the building's life cycle, the activity and interaction between SBs, cities and other entities in the civic ecosystem is unique. Some of these interactions are very similar to those between the city and traditional buildings [33,48]. SBs, on the other hand, offer enhanced interactions due to their advanced energy and digital infrastructures and capabilities. Chan [33] argues that these interactions generate numerous opportunities and value for the smart city, resulting in both direct and indirect benefits. Previous studies have highlighted various challenges and barriers to the adoption of advanced technologies in SBs [37,51]. These include the lack of a clear SC [52] and SB definition [41]; difficulties arising from deficiencies in the city's infrastructure [53,54]; limited knowledge about the benefits of SBs in relation to smart city performance [33,55,56]; a shortage of qualified professionals [57]; undefined basic dimensions of SBs [58]; and a lack of insights for policymakers regarding the impacts of SBs [37]. Additionally, the absence of automated evaluation schemes [37,55] and regulations for achieving a specific level of smartness further complicates the widespread adoption and integration of smart technologies [29,59].

AI is a vast and ever-growing area of research that includes several subfields, methods, and applications, such as machine learning (ML), deep learning (DL), Expert Systems, Natural Language Processing (NLP) [44], Large Language Models (LLMs) and generative chatbots [60]. Within the realm of smart cities, AI utilizes sophisticated algorithms to allow machines to replicate human intelligence, acquire knowledge from data, recognize patterns, and make informed decisions [61]. Alahi et al. [8] stated that the integration of AI, ML, DL, IoT, and Large Language Models (LLMs) in smart city development offers a promising avenue for sustainable urban growth in today's dynamic landscape. LLMs present certain challenges in terms of bias in output, decision-making, and effective utilization [61,62]. However, they hold promise for enhancing natural language understanding and interaction. Wolniak and Stecula [63] highlight the challenges that arise when implementing AI solutions for SBs in smart cities. These challenges include privacy concerns related to the collection and use of personal data, as well as concerns about reliability and safety in the physical context. Issues such as infrastructure limitations, insufficient internet connectivity, or outdated hardware can pose challenges when it comes to implementing AI-powered systems. The authors also proposed sustainable resource management as a potential avenue for integrating AI solutions into SBs. This approach aims to improve resource efficiency and conservation in areas like energy, water, and security. By leveraging AI-powered platforms, communities can be empowered to make informed decisions and actively participate in civic matters. Additionally, this can contribute to environmental sustainability and the adoption of renewable energy sources.

### *2.2. Review of the Existing Evaluation Frameworks for Smart Building Integration into Smart Cities*

Two notable frameworks have been developed to evaluate the integration of SBs into smart cities. The first framework is the SB Integration into a Smart City (SBISC) evaluation framework developed by Apanaviciene et al. [30], which focuses on both the technical and non-technical aspects of SB performance, connectivity, communication, and levels of integration into an SC system. This framework comprehensively assesses SB integration at a certain SC digital platform ICT layer based on [64], and aligns with the logic of the proposed ICT architecture of SC by [65,66] considering various technological aspects such as energy management, infrastructure management, and smart security systems. The SBISC framework aims to define the features that SBs should carry in order to be compatible with the overall context of the SC and to enhance urban living, where it is defined by the SB performance score in each domain of SC based on the level of SB integration into the SC ICT platform, taking into consideration the physical and functional characteristics to their integration with the broader SC infrastructure. Research into the application of the SBISC framework for nine SB cases in different smart cities of the world has shown that it can be used successfully to evaluate SB integration in SC settings, and indicates the potential for future enhancements.

Further improvements are required to address the impact of technological developments and dynamic factors on the long-term integration of SBs. The authors of a Comparative Study of Real Estate Development found that the integration of SB technologies into the SC environment requires careful evaluation and regulation for different stages of SB development [31]. The evaluation of 10 real estate developments has shown that in some cases, the current level of urban intelligence is not sufficient for SB integration at its full potential. Despite the technical advancements of individual real estate projects, their integration into SC networks is hindered by the cities' interoperability capabilities. Hence, revising the framework in response to the emergence of novel information and technology might be necessary.

The second framework evaluating cities and real estate smartness and integration [31] utilizes and expands the main idea of the SBISC evaluation framework analyzed above.

The primary objective of this research is to highlight the significance of characteristics and indicators that enhance the intelligence and integration of real estate projects within the urban setting of smart cities. The framework is organized into seven categories: smart governance, smart people, smart infrastructure, smart energy, smart environment, smart technology, and real estate status. This study examined current SC indexes and SB frameworks to define the benchmarks used to assess the SC and real estate development levels. The criteria for the city benchmark include factors listed in SCI [25], CIMI [28], EU Taxonomy [67], and the studies of Sharifi [68] and Kaluarachchi [69]. The criteria for project levels include a wide selection of indicators from SBISC [30,32], the SB evaluation system [70], and comprehensive studies [71]. Additionally, indexes from other relevant frameworks, online platforms, and other sources including EU Taxonomy [67] and SRI [15] were used as well. The benchmarks function as criteria by which the chosen cities and real estate development initiatives are assessed.

In addition, the research determines the designation of SC as the initial phase, followed by identifying a smart project within the chosen city. The selection criteria at both levels were devised to assess the present condition of prominent smart cities and real estate, pinpoint areas requiring enhancement, and provide attainable objectives for cities and projects in the current smart market. The real estate standards were chosen based on six factors and ten key aspects for the selected smart cities. Nevertheless, executing the methodological framework may raise challenges because of the wide range of categories and indicators involved. Furthermore, the research emphasizes that there is room for enhancement on both the urban and project levels, indicating that the framework may not encompass all facets of intelligence and integration.

These frameworks provide distinct insights into the assessment of smart cities and the development of real estate. The wide number of categories and indicators makes it difficult to offer clear instructions on how to prioritize or provide varying weights to distinct signals within a framework, which can make implementing this rule problematic. Moreover, the analysis of real estate and smart cities does not particularly address the environmental and sustainable effect elements. Nevertheless, more adjustments may be required to effectively handle the current limits and restrictions.

Domingos et al. [29] presented a new assessment framework for SBs in the context of smart city development. They emphasized the importance of adopting a unified approach in both the design and evaluation of SBs within the broader smart city context. The authors highlight the significance of incorporating several aspects, such as environmental sustainability, building attributes, intelligence, computational management, and analytics, in order to improve the efficiency and sustainability of SBs. This holistic approach ensures that all aspects of SB functionality are considered and improved, leading to increased efficiency and environmentally sustainable urban growth. The absence of standardization poses a challenge when it comes to comparing different projects and drawing broad conclusions across diverse urban contexts. Assessing the challenges of integrating SBs into the broader smart city ecosystem is no easy task. Rodríguez et al. [72] highlighted the importance of implementing methods and analysis tools such as GIS and AI that can assist cities in achieving sustainable urban planning and contribute to the overall resilience of urban environments, where the citizen can manage their growth, protect natural resources, and improve the quality of life for their inhabitants. Nevertheless, they stress the significance of considering various aspects of urban transformation in this process. The complexity of capturing the dynamic interactions and rapid technological change between SBs and various urban systems often poses challenges [73]. Due to the rapid pace of change, assessment frameworks can quickly become outdated, resulting in evaluations that may be inaccurate or irrelevant. Therefore, existing methodologies frequently face challenges when it comes to evaluating the long-term intelligence and effectiveness of buildings in ever-changing urban environments. This limitation is especially noticeable when considering the requirement for longitudinal studies and lifecycle analyses. These types of studies are resource-intensive and often go beyond the capabilities of many existing assessment frameworks. The current integration of smart initiatives within the sustainable development, green, and resilience objectives of smart cities is not well-defined, and there is a lack of a clear methodology available to assess the implementation of strategies [58].

### 2.3. Application of AI and Advanced Technologies for Smart Buildings and Smart Cities

Recent research has emphasized the crucial significance of AI applications in enhancing operational efficiency and user satisfaction in SBs and SCs [44,74–77]. AI-based modeling is essential for creating automated, intelligent systems that mimic human intelligence processes using computer systems. This includes expert systems, NLP, speech recognition, and machine vision. AI includes several qualities, such as analytical, functional, interactive, visual, and textual, as outlined by Sarker [78]. Merabet et al. [79] provided an overview of advanced AI tools used to improve thermal comfort in indoor environments. This review focuses on the development of thermal comfort prediction models using various ML algorithms and their integration into building control systems to improve energy efficiency. Estebsari and Rajabi [80] presented the DL model to predict residential energy consumption based on electrical loads. The shortage of applications for nonelectrical energy loads may be due to the additional time and expense required to obtain thermal, lighting, and/or natural gas data. Despite the current state of uncertainty and volatility, predicting energy loads at a detailed level has become more challenging. However, when there are changes in environmental factors such as temperature, humidity, emissions, water pollution, noise, and other variables, SB systems can detect abnormalities and respond quickly [81]. The safety of the occupants is a paramount concern when it comes to building operations. One effective way to achieve this is by implementing visual systems and sensors. Research on the effectiveness of AI in improving safety precautions in SBs has uncovered various applications and benefits for fire detection systems [82], hazard detection [83], and the recognition of perilous chemical pollutants [39].

Human–computer communication might be enhanced by using Natural Language Processing, which is a subfield of artificial intelligence [84]. Natural language processing algorithms are developed to teach computers how to understand and produce human language [78,85]. New NLP applications have been created for emotional analysis, text synthesis, information extraction, language translation, and answering questions, and have attracted considerable interest [86]. According to Tyagi and Bhushan [87] and Kim et al. [88], NLP demonstrates a significant breakthrough in enhancing human–building interactions and optimizing building automation systems. Seamless and uninterrupted communication between people and SB systems enables the creation of environments that are personalized and flexible [89]. Natural language processing models enable user-friendly interfaces for IoT applications in SBs and workplaces [90].

Natural language processing approaches are also crucial in SC administration for enhancing communication between humans and machines by analyzing unstructured textual data [91,92]. Scholars have used NLP to create algorithms for real-time event detection, like accidents, natural disasters, and public gatherings. As an example, they are used to analyze repetitive calls made to public safety agencies in order to identify the primary factors contributing to these calls [93]. They aim to improve the coordination of event detection systems with other city services to enhance governance effectiveness [94,95]. Existing project management models that forecast project performance and risks are based on specific unchanging characteristics such as project type and bidders' revenue. NLP improves models by supplying them with in-depth information extracted from text data, including project descriptions and feedback from stakeholders [85,96]. The B-SMART model by Genkin and McArthur [89] demonstrates advanced AI approaches, namely in the field of NLP, for interacting with several external entities within a building system. This entails using NLP models to enhance communication between tenants and the SB. Tenants can contact the building supervisor to discuss issues, link self-driving cars to the building to monitor parking availability or charging stations, and engage with other intelligent buildings via a connected smart grid. The primary benefit of this method is that NLP-based communication may be easily comprehended and reviewed by humans. In the context of smart city ICT, NLP plays a significant role by being utilized in several aspects of smart city design such as data gathering, user interface, and the functional layer, as stated by Tyagi and Bhushan [87]. The progress made, along with continuous studies on NLP and AI, could greatly enhance efficiency, sustainability, and general quality of life in SCs globally. By integrating AI methods with NLP, computers can analyze, comprehend, and deduce meaning from human speech or text, which can be beneficial for constructing textual AI models.

The emergence of LLMs represents an enhanced extension of AI capabilities in transformer-based models such as GPT-3 and GPT-4 [97], which are deep learning-based NLP models that use extensive data to understand the structure, sentiment, and context of a language. The output of this approach is of exceptional quality, reflecting the precision and clarity of the instructions given. In recent years, cities have adopted the use of AI to analyze and study various factors including air quality, traffic patterns, population trends, weather conditions, and more [76,81,84,98]. In the field of deep learning, the feasibility of an approach to incorporating LLM and AI-generated data into urban energy modeling is intriguing and vital area of research [99]. The study conducted by Shoaib et al. [100] highlights the considerable benefits of utilizing LLMs in intelligent transportation systems. By employing social media sentiment analysis, this system can greatly improve various aspects including traffic analysis, emergency response and disaster management, multimodal transportation planning, and traffic forecasting. The LLMs demonstrated their ability to evaluate historical traffic data, meteorological circumstances, and exceptional events as well. Through the examination of data originating from a variety of sources, these algorithms effectively regulated traffic in real time, and promptly produced emergency alerts and warnings. As a consequence, they expeditiously provided the transportation sector with up-to-date information.

Thus, LLMs have revolutionized NLP with their ability to generate human-like text through extensive training on large datasets. It is becoming a crucial field of study in artificial intelligence, and can transform the manner in which humans engage with and comprehend language. These models, including OpenAI ChatGPT-3.5, GPT-4, and Google Bard, have been employed by academics and in industry. Smart data analysis and interpretation using sophisticated NLP improves decision-making and textual understanding; the tool can facilitate the user's extraction of valuable insights from research papers and reports. This, in turn, can contribute to establishing a comprehensive knowledge base that will ground an evaluation framework for SB integration into SC development.

## 3. Methodology

### *3.1. Theoretical Framework for Smart Building Integration into Smart City*

This section outlines the methodology that employs advanced AI tools to evaluate SB integration into a smart city. For the theoretical basis, the authors use the conceptual framework produced in their prior research to explore the SB's compatibility with the SC's performance [5], as presented in Figure 1.

The process of integrating SBs into smart cities involves the seamless integration of SBs into the wider urban infrastructure and ecosystem. In a smart city, the digital infrastructure provides considerable opportunities for improving the efficiency of municipal operations, strengthening resilience capacity, and ensuring the sustainability of the environment. Thus, three primary aspects have been selected to evaluate the performance of smart cities (Table 1).

This framework's strength lies in the complex interdependencies between SBs and various smart city domains. Five SC domains were selected as interrelated between the SB and SC: smart energy, smart mobility, smart water, smart waste management, and smart security. The selection of domains was based on examining different current categories, considering the significant interconnectedness and technical features between SBs and SCs. The description of each domain is provided in Table 2.

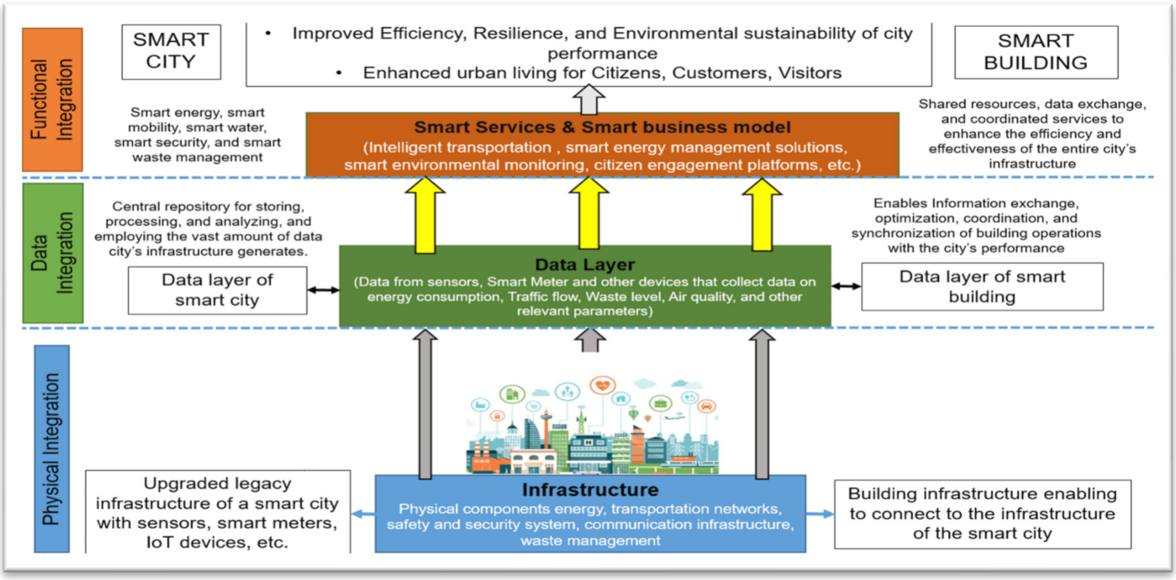


**Figure 1.** Conceptual framework of smart building integration into a smart city [5].

**Table 1.** Smart city performance evaluation aspects [5].

| SC Performance Evaluation Aspects | Description |
|---|---|
| Efficiency | Refers to the digitalization of smart cities to optimize resources and processes, resulting in more efficient operations; this then translates into affordability for end users. |
| Resilience | Refers to implementing strategies to strengthen digital infrastructure durability, enhance emergency response mechanisms, and foster community resilience. |
| Environmental sustainability | Refers to the quality of life and efficiency of urban operations and services to ensure that they meet environmental needs. |

**Table 2.** Description of smart city infrastructure domains [5].

| Smart City Domain | Description |
|---|---|
| Smart energy | It encompasses a comprehensive set of services within smart buildings that play a pivotal role in enhancing the overall energy performance of smart cities. It involves advanced technologies and strategies aimed at optimizing energy usage across various sectors, from residential and commercial spaces to transportation and lighting. |
| Smart mobility | A strategic approach within smart buildings and smart cities focuses on optimising transportation systems for heightened efficiency, reduced congestion, mitigated environmental impact, and an elevated quality of life. |
| Smart water | Encompass various set components of technologies and strategies designed to enhance the sustainability and efficiency of water usage in smart buildings and contribute to overall water management performance in smart cities. |
| Smart waste management | An innovative approach utilizing technology to handle waste throughout its life cycle, encompassing monitoring, collection, transportation, processing, recycling, and disposal to promote sustainable practices, including recycling and closed-loop economies. |
| Smart security | An integral system that leverages IoT technology enables real-time identification, tracking, and reporting of security-related incidents, leading to improved safety measures and efficient emergency response. |

A smart building is considered to be integrated into a smart city if it is connected to SC infrastructure and shares resources, data and coordinates, and synchronizes the SB operation with the entire SC performance. This integration enables the creation of smart services and smart business models within the SC ecosystem (Figure 1).

Different SBs might be integrated with different SC infrastructure domains. Therefore, an SB's integration into SC performance might be evaluated by using intelligent service variables, which have been identified in the previous research study through an examination of the existing literature and case studies [5]. These 26 factors describe the smart features of the SB, and are related to five SC infrastructure domains (Table 3). This approach provides a more comprehensive insight into how various SB technological factors influence the score of SB integration into SC, and enables an assessment of the impact of these factors on the efficiency, resilience, and environmental sustainability of SC performance.

### *3.2. Methodology for Employment of ChatGPT-3 and Bard Models as Artificial Intelligence Experts*

Although human evaluation is considered the gold standard, as addressed by [101], Chen et al. [33] concluded that human assessment could be time-consuming, expensive, scaled-out, inconsistent, and non-replicable.

ChatGPT-3 and Bard models are LLMs of sophisticated DL systems capable of executing a wide range of NLP tasks (Figure 2). LLMs utilize transformer models, which are DL models that rely entirely on self-attention layers. These models are trained using extensive text datasets. LLMs have the ability to mimic the human brain: to identify, convert, anticipate, or produce written or other forms of information. To achieve this, they undergo a two-step process: pretraining and fine-tuning. This enables them to perform tasks such as classification, question answering, and text generation [101]. LLMs are used in various NLP applications, including translation, chatbots, and AI assistants. There are three main types of LLMs: generic or raw language models, dialogue-tuned language models, and instruction-tuned language models [102]. In this research, the focus is on instruction-tuned language models, which are trained to predict responses based on instructions given in the input. This enables them to conduct sentiment analysis or produce text or code.

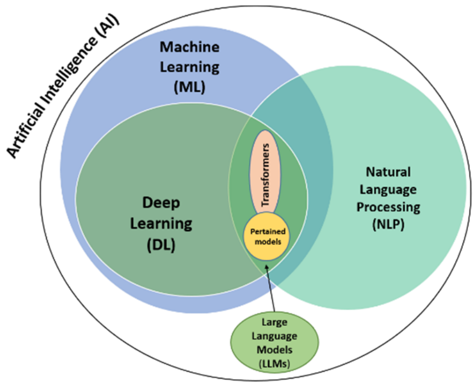


**Figure 2.** Integration of LLMs within AI subfields (adopted from [103]).

The importance of LLMs in evaluating the factors of SBs' significance in smart cities lies in their architecture's ability to understand text that resembles human language. The growing use of LLMs in sentiment analysis (SA) has enabled them to efficiently assess textual data and forecast sentiment ratings [104], including positive, negative, or neutral feelings. SA encompasses a range of different methodologies, each characterized by a unique approach and specific usage. A prominent form of SA is fine-grained SA, which involves assigning sentiment scores on a scale ranging from 1 to 5 [105]; the implementation of this type of SA necessitates the use of Large Language Models (LLMs) to engage with the prompt in order to produce evaluation scores.

**Table 3.** AI-based evaluation framework for smart building integration into smart city.

| Smart City Infrastructure Domain | Smart Building Services Factors | Impact on the Smart City Performance: Efficiency | Impact on the Smart City Performance: Resilience | Impact on the Smart City Performance: Environmental Sustainability | Impact on the Smart City Performance | Factor Score | Smart City Infrastructure Domain Impact, % |
|---|---|---|---|---|---|---|---|
| **1** | **2** | **3** | **4** | **5** | **6** | 7 | **8** |
| Energy | Electrical Energy Storage (Battery) | 2 | 2 | 1 | 5 | 25 | |
| | Shared Electrical Energy Storage | 2 | 2 | 1 | | 25 | |
| | Ability to Work Off-Grid (renewable energy sources: solar, wind) | 1 | 2 | 1 | | 20 | |
| | Energy Usage Monitoring and Control, Demand-Side Management | 2 | 1 | 2 | | 25 | |
| | Smart Heating, Cooling, and Hot Water Preparation | 2 | 2 | 2 | | 30 | |
| | Thermal Energy Storage | 2 | 2 | 1 | | 25 | |
| | Shared Thermal Energy Storage | 2 | 2 | 2 | | 30 | |
| | | | | | | **180** | **32.67%** |
| Mobility | Smart EV Charging | 2 | 1 | 2 | 4 | 20 | |
| | Carpooling/Ride Sharing | 2 | 1 | 2 | | 20 | |
| | Smart Parking Management System (parking application, e-Parking) | 2 | 1 | 1 | | 16 | |
| | Shared Parking Space | 2 | 0 | 1 | | 12 | |
| | Online Video Surveillance | 1 | 2 | 1 | | 16 | |
| | Last Mile Driving | 2 | 0 | 1 | | 12 | |
| | | | | | | **96** | **17.42%** |
| Water | Smart Water Mixtures | 2 | 1 | 2 | 4 | 20 | |
| | Smart Water Monitoring and Shut-Off (leak detection and prevention) | 2 | 2 | 2 | | 24 | |
| | Smart Water Irrigation System | 2 | 1 | 2 | | 20 | |
| | Smart Water Meter | 2 | 1 | 2 | | 20 | |
| | Greywater Recycling | 2 | 2 | 2 | | 24 | |
| | Rainwater Collection (harvesting) and Reuse | 2 | 2 | 2 | | 24 | |
| | | | | | | **132** | **23.96%** |

**Table 3.** *Cont.*

| Smart City Infrastructure Domain | Smart Building Services Factors | Impact on the Smart City Performance: Efficiency | Resilience | Environmental Sustainability | Impact on the Smart City Performance | Factor Score | Smart City Infrastructure Domain Impact, % |
|---|---|---|---|---|---|---|---|
| Waste Management | Smart Waste Containers (smart bins) | 2 | 1 | 2 | 3 | 15 | |
| | Automation and Robotic Waste Collection (underground waste collection) | 2 | 2 | 2 | | 18 | |
| | | | | | | **33** | **5.99%** |
| Security | Smart Monitoring and Data Analytics of the Surrounding Environment (face detection, car plate detection) | 1 | 2 | 1 | 5 | 20 | |
| | Smart Fire Management | 2 | 2 | 1 | | 25 | |
| | Disaster Event Communication Management | 2 | 2 | 1 | | 25 | |
| | Smart Security Lights | 1 | 2 | 1 | | 20 | |
| | Integrated Sensor Solutions | 1 | 2 | 1 | | 20 | |
| | | | | | | **110** | **19.96%** |
| | **Ideal Integration Score** | **47** | **40** | **39** | **21** | **551** | **100%** |

The method of training LLMs for SA consists of multiple distinct steps [106]: collecting a significant quantity of textual data, and thereafter utilizing these data to train the model. Data are gathered from several sources, including webpages, information, reports, and publications [101]. According to [107], ChatGPT-3 was taught using a semi-supervised technique known as Reinforcement Learning from Human Feedback (RLHF). The training data comprised 300 billion tokens, sourced from several channels, including 60% from websites, metadata and text extraction, 16% from books encompassing science and literature, and 3% from Wikipedia. On the other hand, the Bard neural network is trained using a comprehensive dataset named Infiniset [108], which encompasses an immense volume of information. The model has undergone training using a vast amount of data, including 2.9 billion documents, 1.12 billion dialogues, and 13.39 billion data points. In order to maintain its applicability, it consistently retrieves and incorporates data from the internet. This encompasses a wide array of sources, including public forums, code documents from programming-related websites, Wikipedia, English web pages, and non-English web publications. During the pre-training process, both models are trained to predict the following word based on the preceding words in a sentence, and so they have the capability to learn facts, syntax, and some level of reasoning via an unsupervised learning process. In addition, the models undergo fine-tuning on more specific datasets that include human feedback. In this way, the models acquire the ability to understand and generate text by virtue of their ability to predict the subsequent word in a phrase.

Once the model has completed its training, it can be further enhanced to better suit certain applications, such as sentiment analysis. The model is trained on a more limited dataset that is tailored to the precise job being addressed. This allows the model to comprehend the distinct patterns and complexities linked to the assignment. The model offers a sentiment score that aids in comprehending the overall sentiment of the text. Consequently, the utilization of sentiment analysis by LLMs is facilitating a more precise examination of public sentiment on a vast scale.

LLMs are trained on data that mirror the biases present in the real world, and as a result, they may accidentally perpetuate these biases in their predictions. This is one of the biggest limitations that are often considered. The concept of bias refers to the presence of systematic misrepresentations, attribution errors, or factual distortions that can lead to favoring certain groups or ideas, perpetuating stereotypes, or making incorrect assumptions based on the learnt patterns [109]. There are several ways to address biases in LLMs, such as fine-tuning them with fairness objectives, post hoc debiasing, and debiasing the training data by removing or correcting biased data from the training set [110], which is implemented in this research by training both AI models through five sessions with different time frames in the context of responses generated. In addition to biases, the incorporation of AI into the evaluation of city projects raises concerns about ethics, transparency, accountability, data privacy, and misinformation. Planners increasingly depend on AI for decision-making, raising concerns about the potential of these systems to reinforce bias, obscure decision-making processes, and compromise privacy. These issues have the potential to erode public trust and exclude marginalised communities [110,111]. Therefore, the inclusion of human experts in AI model development and decision-making processes can offer crucial contextual understanding and ethical judgement that AI models may lack. The participation of humans in the quality control process can be very beneficial. They can detect biases, errors, and unintended consequences in the output of the AI model. By providing valuable feedback, humans contribute to enhancing the performance and fairness of the model. Furthermore, incorporating stochastic models such as chance-constrained programming (CCP), as described by [112], could address the uncertainties in the advanced AI models.

The evaluation framework methodology employs two widely known Large Language Models, namely, Google's Bard and OpenAI ChatGPT-3, as AI experts to assess the impact of selected SB services on SC performance and the importance of their domain in SC. Bard (Gemini), Google's LLM, was created to enhance language understanding and improve user interactions, while utilizing for the training process the vast language databases available to Google [113]. OpenAI ChatGPT-3, on the contrary, places a strong emphasis on democratizing AI, particularly in the realm of generating written content. There are several requirements taken into consideration when selecting between the two AI models, which are: contextual comprehension requirements, integration standards, conversational fluency, and the overall goals of the application or project [114,115]. The text evaluation capabilities of LLMs have been greatly enhanced by recent advances in deep learning. The potential use of the Google Bard and ChatGPT-3 models in sentiment analysis (SA) was also demonstrated in recent studies [116,117]. The sentiment analysis approach, also known as opinion mining, uses AI techniques to extract subjective viewpoints, sentiments, and opinions from textual data [118].

The evaluation methodology utilizes the analytical capabilities of Google Bard and OpenAI ChatGPT-3 models to ensure a comprehensive assessment of how SB services align with SC's performance goals. The provided prompts include the descriptions of SB factors, definitions of SC performance elements, and SC infrastructure domains, as outlined in the paper by Apanavičienė and Shahrabani [5]. They also include a proposed rating system to identify the impacts of factors of SB services, and a suggested rating system for the importance of the five primary SC domains.

During the performance assessment, each factor within the domain was assessed for its influence on three aspects of SC performance: efficiency, resilience, and environmental sustainability. The impact of each SB factor is assessed using a scale ranging from 0 to 2, where 0 denotes no impact, 1 denotes moderate impact, and 2 denotes significant impact. Regarding the significance of SC infrastructure domains, each domain is allocated a collective weight according to its importance using a 5-point Likert scale; range 1—not important to 5—significant important. The weight represents the relative importance of each domain in the context of the overall performance of smart cities, where a higher weight signifies increased significance. The responses produced by OpenAI ChatGPT-3 and Google Bard represent the influence of each element, determined by a detailed prompt that includes all required instructions. We repeatedly tested each model in five different sessions, each consisting of five trials, with the same tasks to mitigate bias issues, and then analyzed the responses by taking the mean value of these sessions for each model. This analysis generated a distribution of possible impact scores, as well as the probability of each score. This approach allows for a more detailed understanding of the model's predictions and the level of confidence in those predictions. We then summarized the results by calculating the mean index for the two datasets generated in the previous step, as shown in Table 3. Furthermore, to assess the reliability of the results presented in Table 3, the research underwent two rounds of a validation process that involved expert judgments, as described in Section 3.3.

#### 3.2.1. OpenAI ChatGPT-3 Model Employment

ChatGPT-3 utilizes a transformer model, specifically the GPT (Generative Pre-trained Transformer) architecture, which incorporates self-attention mechanisms to grasp the context of sentences. This architecture enables the model to generate text that is cohesive and contextually appropriate. The OpenAI Text-Davinci-003 AI model is accessible through the Chat Generative Pre-Train Transformation (ChatGPT) API, which also enables effective SA performance. The training method of the Text-Davinci-003 model involves several stages, one of which is pre-training on a vast corpus of text data obtained from the internet. The objective of this phase of unsupervised learning is to teach the model to comprehend the complexities and patterns of human language by predicting the subsequent word in a phrase. Training data consisted of diverse sources, such as books, articles and websites, enabling a thorough understanding of many themes and writing styles. After undergoing pre-training, the model is further enhanced through fine-tuning on more specific datasets. This phase involves supervised learning when the model is trained to follow particular instructions and generate text that matches the required output. Fine-tuning the model can improve its performance on certain tasks, ensuring that it adheres to user instructions [104,107].

SA in Python ChatGPT APIs is carried out by the ChatGPT-3 API via a series of phases. Initially, an API key must be obtained from the OpenAI website. Because it establishes use limitations and grants access to OpenAI users' accounts, this key is regarded as private. Installing the OpenAI Python module after that will provide an easy-to-use interface to communicate with the OpenAI API. Lastly, SA is operated using the Text-Davinci-003 paradigm of the ChatGPT-3 API, and prompts are provided via libraries. In this phase, the API response generation is determined by several parameters, as follows:

1. Engine—This parameter determines the language model to be utilized. The Text-Davinci-003 model has been employed for this purpose. This model is developed by OpenAI and is categorized as a language model belonging to the GPT-3 (Generative Pre-Trained Transformer 3) model family, and is considered a robust and adaptable model. The model was created to generate text that mimics human language, using given prompts (Supplementary Materials) and demonstrating the capacity to understand and respond to natural language queries;
2. Temperature—This option governs the level of ingenuity in the response when it is set to 0, indicating that the model will consistently produce the most probable answer;
3. Max_tokens—The operational methodology for the Text-Davinci-003 model involves providing a prompt or direction to the model, which then generates a textual output in response. The maximum response length parameter allows the model to accurately evaluate and understand complex language structures. The model's context window can include up to 4097 tokens, allowing it to process more data and generate more comprehensive responses. Nevertheless, this size is sufficient to encompass all the responses about the chosen components of SB services and their primary domain, which is the SC infrastructure domain.

Upon submitting the request to the ChatGPT-3 API and receiving a response according to the prompt instructions, the model produces the output outcomes in CSV format, which is kept on the PC hard disc for subsequent analysis and computation, as depicted in Figure 3.

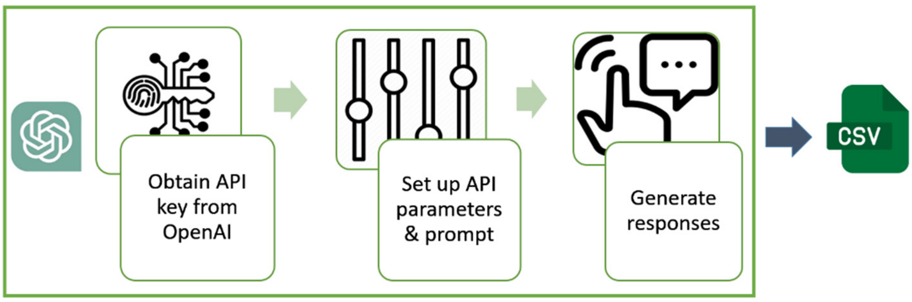


**Figure 3.** Open AI ChatGPT-3 model application.

#### 3.2.2. Google Bard Model Employment

Google Bard (lately renamed Gemini) is an LLM that was recently introduced in response to the growing rivalry in the field of AI; it is built on Google's conversational AI framework LaMDA (Language Model for Dialogue Applications). LaMDA places significant value on conversation, and aims to deliver responses that are engaging, informative and relevant. Thus, it simulates an authentic dialogue with a human user. It employs NLP and ML algorithms to deliver precise and useful responses to diverse queries. A Python module called Bard-API provides an easy-to-use interface for working with Google Bard. This module improves existing applications and workflows by smoothly integrating Google Bard into Python settings, which provides data scientists and developers with considerable benefits. The Bard-API streamlines duties such as answering questions. The responses to all queries sent to Google Bard using the Bard-API are provided in natural language as follows:

1. Configuring the Bard API. The Python package offers an API connection interface to Google Bard, enabling Python scripts to retrieve responses from Bard and pose questions to the Google Bard Chatbot;
2. Configuring the prompt and API key. An accurate prompt (Supplementary Materials) has been established, encompassing numerous lines that explicitly outline the task for the Bard API. Because of the dataset type that the two models are trained on, the same information is used in the ChatGPT-3 prompt but in a different structure and with more details. Therefore, the prompt provides comprehensive information and instructions for obtaining responses. It includes definitions and objectives of SC performance, as outlined in Table 1. Additionally, it explains each of the SC infrastructure domains, which is crucial for assessing the relative significance of the primary domain using a Likert scale. This context offers a comprehensive explanation for each domain, including keywords associated with smart cities. These keywords include smart grids and energy efficiency for the energy domain, smart traffic management and sustainable transportation for mobility, efficient water distribution networks and water conservation measures for the smart water domain, waste reduction and recycling initiatives, cyber security measures, public safety initiatives, and surveillance systems for waste and security systems, respectively. Furthermore, each domain explanation includes a comprehensive list of factors associated with each component, as reported in the prior study [5]. Subsequently, a concise directive is presented at the end of the prompt to elicit a direct response without more elaboration, while ensuring that all weight values are maintained as whole numbers;
3. Function for making an API call and extracting data. During this phase, the script utilizes the Bard to initiate an API request, passing the specified API key and the prompt as parameters. This is done to facilitate the transmission and reception of a response. The Bard-API will analyze the given prompt and provide a written response. It is essential to establish a valid session every time the model is executed to safeguard sensitive data and guarantee that only authorized users can engage with the system, as depicted in Figure 4.

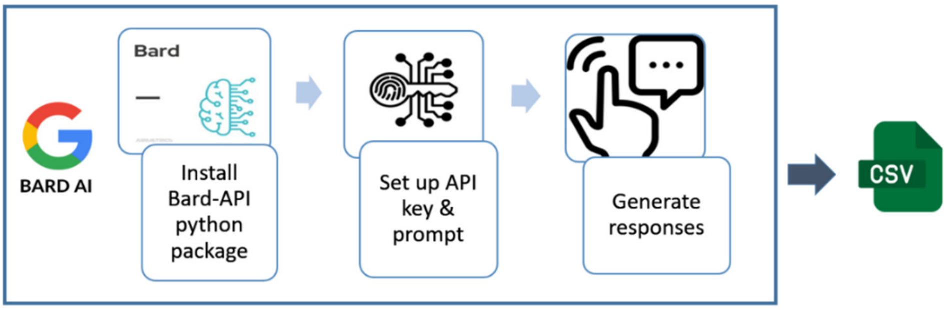


**Figure 4.** Google Bard model application.

### *3.3. Framework Validation*

A Delphi method was selected to carry out the validation of the proposed framework; it is a systematic and repetitive process that has the capacity to achieve collective agreement and collect points of view from human experts on a complex subject [119]. This technique describes the procedure for conducting a Delphi survey that specifically examines the integration of SB into the SC evaluation framework. The Delphi process consists of several rounds, and aims to validate the proposed evaluated framework using AI tools for integrating SBs into SC by reaching a consensus among human experts.

An expert panel is chosen based on their expertise and experience in the areas of SBs, smart cities, urban planning, and related disciplines. The selection criteria encompass academic credentials and scientific research in relevant domains, expertise in the implementation of smart city initiatives and/or SBs, and contribution to the pertinent literature and industry standards.

The Delphi survey was carried out using an online questionnaire utilizing Google Forms to guarantee participant confidentiality and facilitate accessibility. The process involves the completion of two sets of questions. Round 1: Preliminary examination of the assessment framework. Round 2: A process of reevaluating or confirming the first responses in order to reach the defined level of the agreement. The Round 1 questionnaire included the gathering of qualitative data, including comments regarding any uncertainties, the scope of coverage, constraints, and potential areas for framework improvement. The evaluation of the AI-based framework assessment involved quantitative data. The experts were asked to indicate their level of agreement, partial agreement, or disagreement with the impact and importance of the criteria. Experts assessed the importance of the primary domain and evaluated the impact of each element. The factors and domains that failed to achieve the defined consensus level necessitated further validation. Round 2 comprised the following: providing feedback from the first round and the evaluation of criteria that did not achieve the designated consensus in Round 1.

The Delphi method offers a systematic approach to obtaining expert consensus on the evaluation framework for the integration of SBs into a smart city. The iterative method guarantees that a wide range of expert viewpoints are considered, resulting in a strong and validated framework.

## 4. Results and Discussion

### *4.1. Development of AI-Based Evaluation Framework for Smart Building Integration into a Smart City*

#### 4.1.1. Employment of ChatGPT and Bard Models as Artificial Intelligence Experts

This section presents the evaluation framework, including the performance metrics and insights obtained from the selected AI models. The assessment of SB service features and infrastructure domains' impact on SC performance involves a systematic and multifaceted method that leverages the capabilities of OpenAI ChatGPT-3 and Google Bard.

ChatGPT-3 consistently assigned a score of 2 for both efficiency and resilience for all factors of SC infrastructure. Nevertheless, the score for environmental sustainability fluctuated among these SC domains. In contrast, Google Bard demonstrated a wider range of scores in all three SC performance areas, with specific factors obtaining lower ratings in resilience and environmental sustainability. This could be related to Google Bard being trained with a dataset containing real-time authentic information and accessing up-to-date information through Google search [45,120], while ChatGPT-3 demonstrates superior creativity and outperforms all other LLMs due to its ongoing model refinement processes performed through human feedback. Nevertheless, the disparities between both models do not clearly indicate the substantial advantage of one model over the other. Both AI models were executed five times with varying time frames to address the issues of biases. Nonetheless, LLMs are difficult and demanding, as the language's inherent character as well as extrinsic biases significantly influence the creation and development of such models, as discussed by [62,104]. Biases can originate from diverse sources, including the training data, the fine-tuning procedure, or even the human reviewers themselves. Nevertheless, the integration of ML methodologies with human experience presents a potentially effective approach to tackling the challenges arising from biases in generative language models [62].

Both AI models can efficiently handle and examine substantial amounts of data derived from diverse origins. The datasets comprise academic literature, books, industry papers, reports, real-world experiences, and case studies; thus the selected LLMs successfully employed these data to comprehend the influence of many aspects on the performance of smart cities. The combination of the two models is conducted by aggregating the values obtained and rounding them to an integer number so as to eliminate digitals and then calculate the factors impacting the SC performance and their infrastructure domain importance. The combined evaluation framework for SB integration into SC developed by applying OpenAI ChatGPT-3 and Google Bard models as AI experts is presented in columns 3–6 of Table 3.

#### 4.1.2. AI-Based Framework Validation

The study used an online two-round Delphi technique to validate and enhance the framework for evaluating SB integration into a smart city. The Delphi approach was selected due to its efficacy in collecting expert viewpoints and achieving consensus on complex topics. Prior to conducting the survey, the Research Ethics Commission of Kaunas University of Technology granted approval No. M6-2023-20 for the project, thus ensuring rigorous quality control and the protection of data privacy.

The Delphi survey using Google Forms involved 14 subject matter experts initially, and 13 in the second round. Such a scenario is commonly encountered in multi-round Delphi investigations [121,122]. Participants were selected on their professional backgrounds, guaranteeing a minimum of five years of relevant experience. The Round 1 questionnaire design consisted of three primary elements. The introductory section included an overview of the framework, elucidating the different elements, and impact evaluations on the efficiency of smart cities enabled by AI generative models like ChatGPT-3 and Google Bard. The evaluations were categorized into five distinct subsections: energy, mobility, water, waste management, and security, which were included in the second portion. Experts were asked to indicate their agreement, partial agreement, or disagreement with smart city factors that impact the performance and their significance within each domain. Additionally, they were asked to suggest additional factors that might be crucial in their opinion for the assessment.

Experts were asked to validate specific factor scores. When there were differences of opinion (partial agreement or disagreement) regarding AI-generated ratings, experts were asked to offer additional evaluations using a three-point scale: 0 (no impact), 1 (moderate impact), and 2 (significant impact). A Likert scale of 5 points (1—less important to 5—very important) was used to assess the significance of each smart city domain. The survey also included open-ended enquiries to explore the clarity, comprehensiveness, constraints, and potential improvements of the framework.

The results from Round 1 were condensed and communicated to the specialists in the second round, with the aim of an 80% agreement consensus. During the first round, a consensus of 80% was achieved for 17 of the 26 attributes that were initially analyzed (Figure 5). However, a comprehensive agreement was not reached for three of the five categories (Figure 5). Factors and domains that did not meet the required standard were designated for further evaluation in Round 2.

In the second round, the participants were given a summary of the results from Round 1, together with the mean values of each factor's importance score as derived from the experts' evaluations, and were asked to reconsider the criteria scores that did not attain consensus or align with the initial evaluations in Round 1. The experts also received individualized feedback on their prior responses to ensure or suggest new evaluation scores that would enable the achievement of a targeted consensus level. After Round 2 (Figures 6 and 7), an 80% consensus level for the remaining nine variables, along with their respective importance domains, was achieved, demonstrating a high level of agreement among experts regarding the evaluation framework.

The Delphi technique successfully enhanced the AI-generated evaluation framework by utilizing iterative expert consensus. Utilizing anonymous feedback and including a two-round procedure enabled experts to enhance their assessments by incorporating collective insights. Controlled feedback methods, such as condensed outcomes, enabled well-informed reassessments. Nevertheless, there are still obstacles that need to be addressed. Withdrawals of participants can have an impact on the robustness of consensus. Subjective evaluations, particularly when it comes to measuring the effect, can create fluctuations. The study faced challenges in reaching an agreement on security variables, emphasizing the necessity of additional research. In summary, the Delphi technique was successfully applied to validate the AI-based framework, showcasing its capacity to boost AI evaluations by including human expert input.

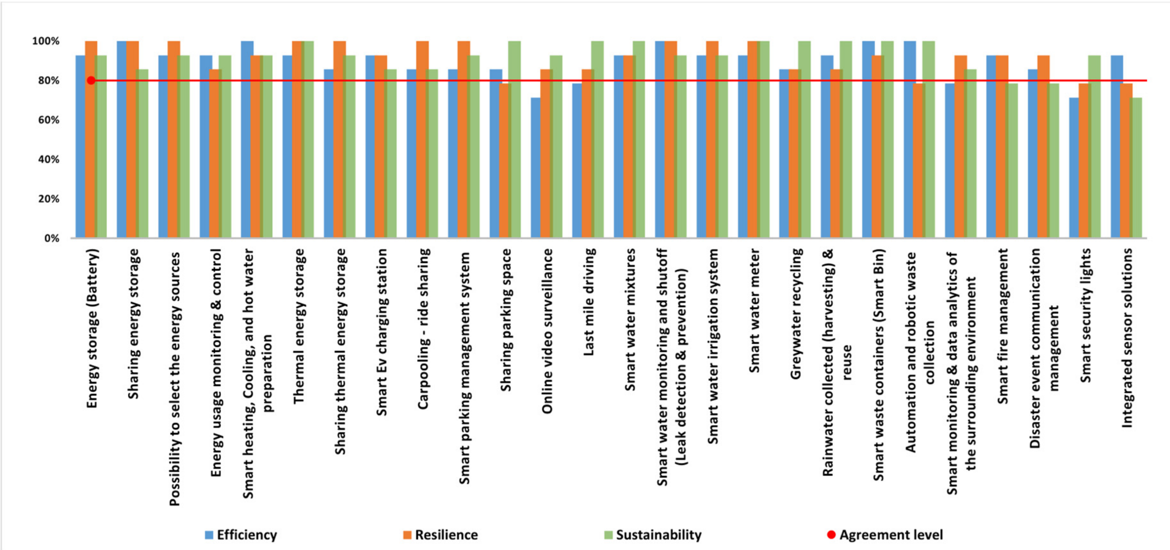


**Figure 5.** Round 1 agreement levels for the smart building service factors.

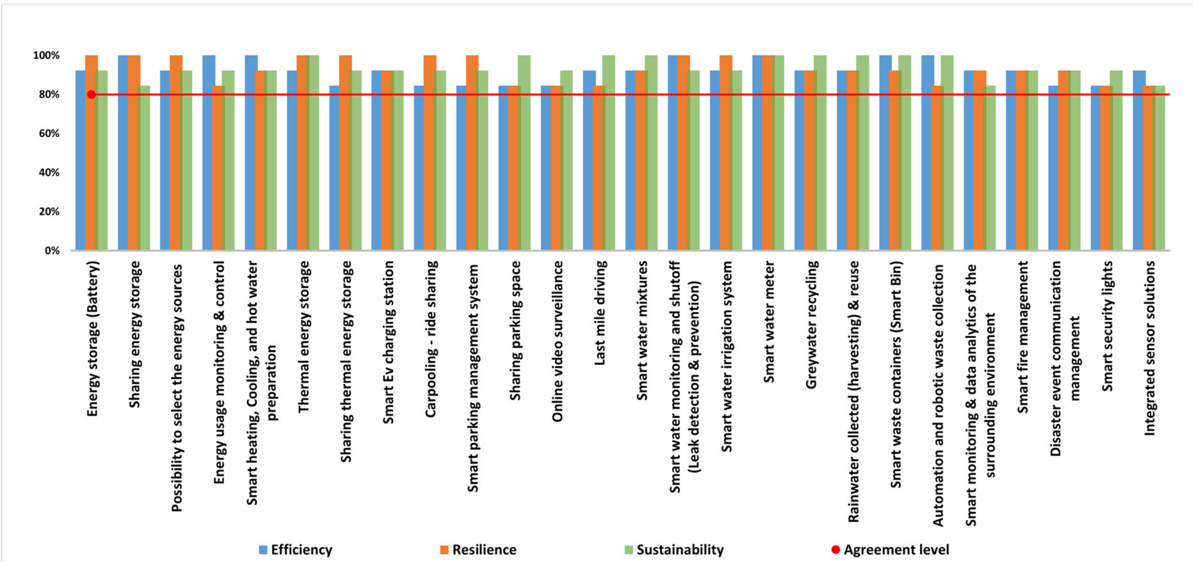


**Figure 6.** Round 2 agreement level for the smart building services factors.

### 4.1.3. AI-Based Evaluation Framework for Smart Building Integration into Smart City

The AI-based evaluation framework for smart building integration into smart cities, validated by human experts, is presented in Table 3. To determine the overall SB integration into SC score (column 7 of Table 3), it is necessary to consider the contribution of each element, depending on its allocated weight, by considering one step in reverse. The factor score is obtained using a mathematical equation by summing the impacts on efficiency, resilience, and environmental sustainability, and multiplying the result by the group weight score, as stated in Equation (1).

$$f_i = \sum_{i=1}^{k} W_i y_i, W_i = [0, 1, 2] \quad (1)$$

where $f$—factor score, $W_i$—smart city performance impacts, $Y_i$—smart city infrastructure domain importance, and $i$—smart city performance aspect.

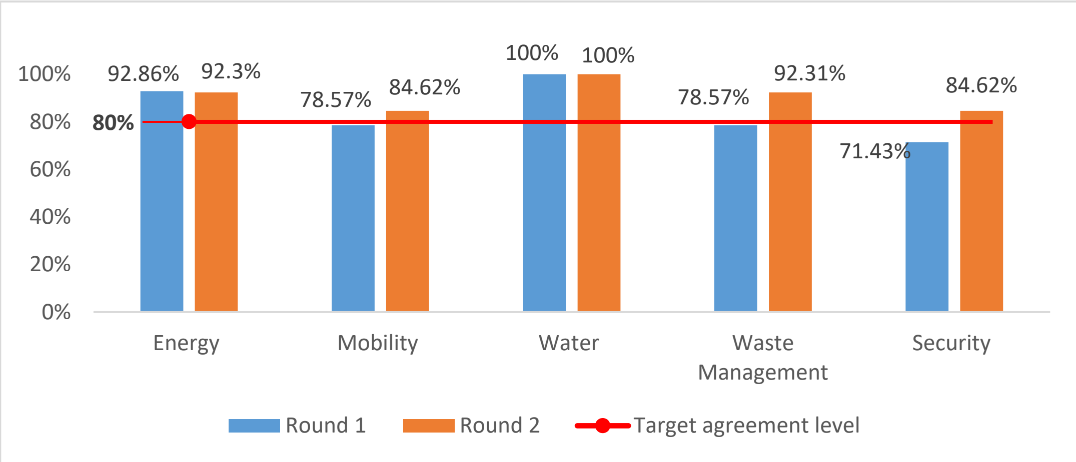


**Figure 7.** Smart city infrastructure domain analysis responses from Rounds 1 and 2.

This calculation yields a composite score, or factor score, that considers the significance or contribution of each component based on its designated weight. The procedure is iterated for each factor to determine its distinct factor score. The factor scores are used to obtain the overall score of SB integration into SC. The 551-point score represents the cumulative points that should be gathered to achieve complete SB integration into an ideal SC. In addition, the totals for each column are calculated to provide a detailed analysis of the efficiency, resilience, and environmental sustainability aspects, respectively.

The cumulative points gathered are contrasted with the ideal integration score for an exemplary SB and SC to determine the degree of integration achieved. Therefore, the evaluation findings are evaluated to understand the strengths and shortcomings of the integration of SB services into SC performance.

The framework depicted in Table 3 enables the overall assessment of the integration of SB services into the infrastructure of SC, as well as quantifying the relevance of an ideal SB's impact on the ideal SC infrastructure domain as a percentage, indicating the highest potential influence on the relative infrastructure domain within the SC framework. These percentages are essential as they provide guidance for decision-making, the allocation of resources, and the identification of the future SB development areas that need further attention or investment related to integration into the ecosystem of a specific SC.

SB services related to the SC energy infrastructure domain are of the highest importance within the framework, since achieving the maximum impact of 32.67% is vital (Table 3). This highlights the necessity of optimizing energy use and incorporating sustainable energy sources into an SB, which are crucial for decreasing carbon emissions and guaranteeing a long-lasting energy provision for the city.

Although it only accounts for 17.42% of the overall factors, SB services related to the mobility domain play a crucial role in mitigating SC traffic congestion, promoting air quality, and improving the city's accessibility by lowering commute time. Notably, smart parking management, along with carpooling and ride-sharing services, are two factors that contribute to this area.

The second most prioritized domain is smart water management services, with an impact of 23.96% on SB integration into SC. Optimizing and preserving water utilization is vital in urban areas, particularly in light of the growing shortage of water resources. The implementation of smart water management practices can result in considerable cost savings and benefits for environmental sustainability, as well as a decrease in water wastage. The significance of smart waste management services is also emphasized. Nevertheless, they only represent a 5.99% impact on the total integration into SC. This highlights the goal of inventive approaches to handle and diminish waste effectively. Efficient waste management is essential for preserving public health, minimizing environmental consequences, and fostering recycling and circular economy initiatives. Moreover, the 19.96% impact of SB services related to the security domain is crucial for guaranteeing the safety and welfare of SC citizens. This includes implementing smart surveillance, fire management, and catastrophe communication, which are vital for creating a resilient urban environment. Thus, the diverse importance of various sectors exemplifies the complex character of smart cities, in which distinct facets contribute to the overall efficacy and prosperity of the urban environment. Therefore, significance percentages serve as a directive to stakeholders to determine the areas in which to concentrate their efforts and expenditures so as to attain the most substantial influence.

### *4.2. Application of AI-Based Evaluation Framework for Smart Building Integration into Smart City: Case Studies*

To illustrate the application of the AI-based evaluation framework for SB integration into Smart City, five sophisticated SB projects were selected as case studies in various geographical locations, and effectively integrated into smart cities: The Edge in Amsterdam, One Angel Square in Manchester, National University of Singapore (NUS) in Singapore, Ongos Valley in Namibia, and Reliance Modern Economic Township (MET) City in India. Criteria were set to ensure that the selected SBs met a variety of smart city goals and development patterns.

The five case studies were chosen to show a range of SB integration initiatives in smart city settings under various development scenarios, urban densities, project scales, and geographic locations. Two prime examples of cutting-edge smart office buildings in densely populated European cities are The Edge in Amsterdam and One Angel Square in Manchester. An example of a smart campus integrated into an urban economic center is the NUS. In a fast-urbanizing African metropolis, Ongos Valley (Windhoek) is an example of a sizable mixed-use development. In conclusion, Reliance MET City (Gurgaon) presents an example of an Indian smart township with an industrial and logistics infrastructure. Because of the variety of situations, the framework's applicability can be thoroughly assessed across a broad spectrum of smart city typologies and development scenarios.

The data for these case studies were collected from many sources. Most projects underwent evaluation by either BREEAM or LEED. Furthermore, prior research has explored these examples to gather primary information on the integration elements identified through literature analyses [5]. The application example of an AI-based evaluation framework for SB Integration into a Smart City is displayed in Table 4, illustrating the case of The Edge smart office building located in Amsterdam. Amsterdam is among the first European cities to adopt the SC concept [123]. The primary objective of The Edge in Amsterdam, the Netherlands, is to function as an example for environmentally friendly and technologically advanced office structures. The Edge, created for Deloitte, was specifically designed to foster collaboration among its employees, while also highlighting the significance of environmental sustainability and intelligent technology in contemporary workspaces, and it has achieved the highest BREEAM score of 98.36%. Additionally, this office space is highly interconnected and technologically advanced, allowing employees to customize their working area via a smart services application [124,125]. The building integrates state-of-the-art elements, and is intended to become a pioneering SB that prioritizes environmental sustainability. It empowers staff to regulate lighting and heating, promoting energy efficiency and environmental stewardship.

The Edge of Amsterdam is distinguished as a prime example of SB integration into SC, achieving a total integration score of 86.75% in SC performance, as seen in Table 4. This demonstrates how intelligent technologies could be used to improve building efficiency and contribute to the wider development of an SC. This is achieved thanks to smart services such as the monitoring and control of energy use, smart management of heating, cooling, and hot water preparation, integrated sensor solutions, and smart EV charging stations. In the resilience of a smart city, the impact of the building is demonstrated by its impressive score of 85.00%, which relates to its robust capability to maintain essential tasks and recover quickly from any disturbances. This is facilitated by services that allow energy storage, smart water monitoring and shutdown, intelligent fire management and communication management during disasters and emergencies, and building operations during disruptions that allow proactive maintenance. The building also has an impressive environmental sustainability rating of 87.18%, and its impact on SC sustainability is remarkable. This score indicates a firm commitment to environmental management by implementing sustainable measures. This can be seen in the integration of sustainable energy sources, with 65,000 square feet of solar panels on the roof and wall surface, greywater recycling and rainwater reuse, all of which help to reduce the sustainable footprint.

The Edge, Amsterdam, stands out with high integration scores compared to the ideal integration model, as illustrated in Figure 8. The analysis shows that The Edge in Amsterdam achieves exceptional performance in the areas of mobility, water, and security, achieving optimal integration ratings in these categories. However, it lacks the highest energy scores and, in particular, waste management, highlighting particular aspects that require further attention and advancement to achieve improvements. These entireties are marked as "N/A" (not applicable) in Table 4. However, according to the study findings, the performance of The Edge is consistent with the SC of Amsterdam, and emphasizes the importance of integration in achieving sustainable urban growth. Consequently, The Edge's success in effectively integrating smart services can serve as an exemplary model for other SBs and cities.

Manchester SC programs aim to use technology to tackle urban problems, improve infrastructure development, and improve the quality of life and adaptability of the urban environment [126]. One Angel Square, a skyscraper located in Manchester, United Kingdom, exemplifies how artificial intelligence and the Internet of Things help the creation of efficient and ecologically sustainable buildings [127]. The building was awarded an outstanding BREEAM rating and integrates many environmental sustainability elements, including rainwater collection, low-energy lighting, and natural ventilation. Building management solutions powered by artificial intelligence have led to outstanding energy efficiency. The functionality of the building aligns with Manchester's SC goals, prioritizing energy efficiency, cutting-edge technology, and environmental sustainability.

One Angel Square exemplifies the capacity of SB to bring about significant change. It showcases that the impact of One Angel Square's integration into Manchester's SC is 55.54%, as demonstrated in Table 5. The most notable gaps are in energy, water, and waste management domains, as presented in Figure 8; thus, significant improvements should be made to reach higher integration scores. Mobility and security domain scores are closer to the ideal, but nonetheless still require additional developments to properly utilize the benefits of SB technology. Rectifying these imbalances will enhance One Angel Square's performance and contribute to the overarching smart city goals of environmental sustainability, efficiency, and resilience.

Nevertheless, some areas require development to completely achieve the smart city's goals. The building features, including energy storage, smart EV charging, and energy usage monitoring, contribute to the efficient use of resources. This is reflected in the 55.32% score (Table 6), which suggests that the building is more than halfway towards achieving the ideal integration impact on the efficiency standard set. The resilience score also stands at 55.00%, indicating that the building has a moderate level of preparedness for dealing with emergencies or disruptions. Features like smart fire management and disaster event communication management contribute to SC resilience. With a score of 56.41%, the building shows a slightly higher contribution to SC's environmental sustainability. This is due to features like the ability to work off-grid with renewable energy sources, rainwater collection and reuse, and smart water metering, which help reduce the environmental impact and promote sustainable practices. Condensed results on SB integration into SC evaluation for all case studies are displayed in Table 5, Table 6, and Figure 8.

**Table 4.** Smart building integration into smart city: The Edge, Amsterdam.

| Smart City Infrastructure Domain | Smart Building Services Factors | Impact on the Smart City Performance: Efficiency | Impact on the Smart City Performance: Resilience | Impact on the Smart City Performance: Environmental Sustainability | Impact on the Smart City Performance | Factor Score | Smart City Infrastructure Domain Impact,% |
|---|---|---|---|---|---|---|---|
| Energy | Electrical Energy Storage (Battery) | 2 | 2 | 1 | **5** | 25 | 22.69% |
| | Shared Electrical Energy Storage | N/A | N/A | N/A | | 0 | |
| | Ability to Work Off-Grid (renewable energy sources: solar, wind) | 1 | 2 | 1 | | 20 | |
| | Energy Usage Monitoring and Control, Demand-Side Management | 2 | 1 | 2 | | 25 | |
| | Smart Heating, Cooling, and Hot Water Preparation | 2 | 2 | 2 | | 30 | |
| | Thermal Energy Storage | 2 | 2 | 1 | | 25 | |
| | Shared Thermal Energy Storage | N/A | N/A | N/A | | 0 | |
| | | | | | | 125 | |
| Mobility | Smart EV Charging | 2 | 1 | 2 | **4** | 20 | 17.42% |
| | Carpooling Ride Sharing | 2 | 1 | 2 | | 20 | |
| | Smart Parking Management System (parking application, e-Parking) | 2 | 1 | 1 | | 16 | |
| | Shared Parking Space | 2 | 0 | 1 | | 12 | |
| | Online Video Surveillance | 1 | 2 | 1 | | 16 | |
| | Last Mile Driving | 2 | 0 | 1 | | 12 | |
| | | | | | | 96 | |
| Water | Smart Water Mixtures | 2 | 1 | 2 | **4** | 20 | 23.96% |
| | Smart Water Monitoring and Shut-off (leak detection and prevention) | 2 | 2 | 2 | | 24 | |
| | Smart Water Irrigation System | 2 | 1 | 2 | | 20 | |
| | Smart Water Meter | 2 | 1 | 2 | | 20 | |
| | Greywater Recycling | 2 | 2 | 2 | | 24 | |
| | Rainwater Collection (harvesting) and Reuse | 2 | 2 | 2 | | 24 | |
| | | | | | | 132 | |
| Waste Management | Smart Waste Containers (Smart Bins) | 2 | 1 | 2 | **3** | 15 | 2.72% |
| | Automation and Robotic Waste Collection (underground waste collection) | N/A | N/A | N/A | | 0 | |
| | | | | | | 15 | |

**Table 4.** *Cont.*

| Smart City Infrastructure Domain | Smart Building Services Factors | Impact on the Smart City Performance | | | Impact on the Smart City Performance | Factor Score | Smart City Infrastructure Domain Impact,% |
|---|---|---|---|---|---|---|---|
| | | Efficiency | Resilience | Environmental Sustainability | | | |
| Security | Smart Monitoring and Data Analytics of the Surrounding Environment (face detection, car plate detection) | 1 | 2 | 1 | 5 | 20 | 19.96% |
| | Smart Fire Management | 2 | 2 | 1 | | 25 | |
| | Disaster Event Communication Management | 2 | 2 | 1 | | 25 | |
| | Smart Security Lights | 1 | 2 | 1 | | 20 | |
| | Integrated Sensor Solutions | 1 | 2 | 1 | | 20 | |
| | | | | | | 110 | |
| | **Collected Points** | 41 | 32 | 33 | | 462 | |
| | **Ideal Integration Points** | **47** | **40** | **39** | | **551** | |
| | **Integration Score** | **87.23%** | **85.00%** | **87.18%** | | **86.75%** | |

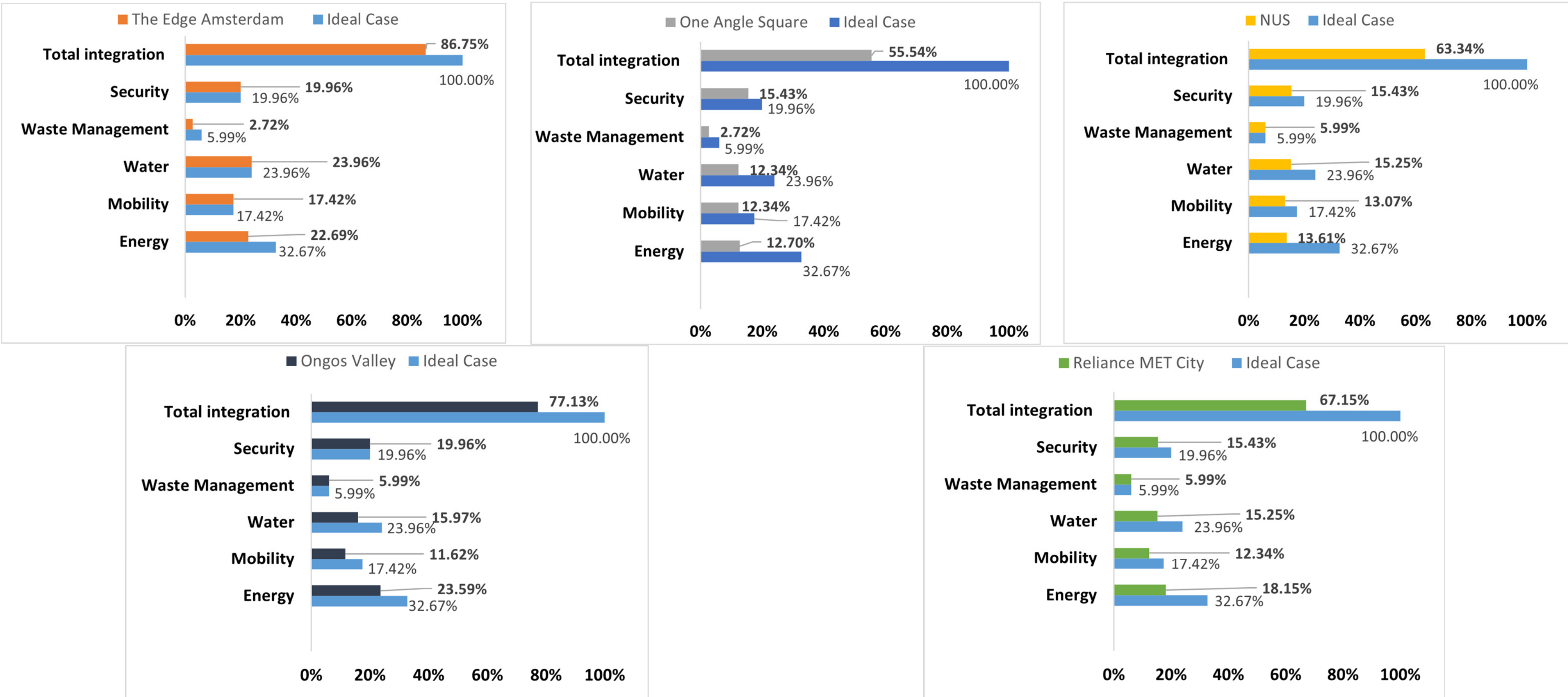


**Figure 8.** The overview of case studies' integration scores.

**Table 5.** Smart building integration into smart city: summarized evaluation results of case studies.

| **Smart City Infrastructure Domain** | **Smart Building Services Factors** | **The Edge, Amsterdam, The Netherlands** | **One Angel Square, Manchester, United Kingdom** | **National University of Singapore, Singapore** | **Ongos Valley Windhoek, Namibia** | **Reliance MET City, Gurgaon, India** |
|---|---|---|---|---|---|---|
| **Energy** | Electrical Energy Storage (Battery) | 25 | 25 | 25 | 25 | 0 |
| | Shared Electrical Energy Storage | 0 | 0 | 0 | 25 | 25 |
| | Ability to Work Off-Grid (renewable energy sources: solar, wind) | 20 | 20 | 20 | 0 | 20 |
| | Energy Usage Monitoring and Control, Demand-Side Management | 25 | 25 | 0 | 25 | 25 |
| | Smart Heating, Cooling, and Hot Water Preparation | 30 | 0 | 30 | 0 | 30 |
| | Thermal Energy Storage | 25 | 0 | 0 | 25 | 0 |
| | Shared Thermal Energy Storage | 0 | 0 | 0 | 30 | 0 |
| **Mobility** | Smart EV Charging | 20 | 20 | 20 | 0 | 20 |
| | Carpooling Ride Sharing | 20 | 20 | 20 | 20 | 20 |
| | Smart Parking Management System (parking application, e-Parking) | 16 | 16 | 16 | 16 | 16 |
| | Shared Parking Space | 12 | 0 | 0 | 0 | 0 |
| | Online Video Surveillance | 16 | 0 | 16 | 16 | 0 |
| | Last Mile Driving | 12 | 12 | 0 | 12 | 12 |
| **Water** | Smart Water Mixtures | 20 | 0 | 20 | 20 | 20 |
| | Smart Water Monitoring and Shut-off (leak detection and prevention) | 24 | 24 | 24 | 24 | 24 |
| | Smart Water Irrigation System | 20 | 0 | 20 | 0 | 0 |
| | Smart Water Meter | 20 | 20 | 20 | 20 | 20 |
| | Greywater Recycling | 24 | 0 | 0 | 0 | 24 |
| | Rainwater Collection (harvesting) and Reuse | 24 | 24 | 0 | 24 | 0 |
| **Waste Management** | Smart Waste Containers (Smart Bins) | 15 | 15 | 15 | 15 | 15 |
| | Automation and Robotic Waste Collection (underground waste collection) | 0 | 0 | 18 | 18 | 18 |
| **Security** | Smart Monitoring and Data Analytics of the Surrounding Environment (face detection, car plate detection) | 20 | 20 | 20 | 20 | 20 |
| | Smart Fire Management | 25 | 25 | 25 | 25 | 25 |
| | Disaster Event Communication Management | 25 | 0 | 0 | 25 | 0 |
| | Smart Security Lights | 20 | 20 | 20 | 20 | 20 |
| | Integrated Sensor Solutions | 20 | 20 | 20 | 20 | 20 |
| | **Total integration score** | **86.75%** | **55.54%** | **63.34%** | **77.13%** | **67.88%** |

**Table 6.** SB integration into SC: SB capacities related to the main SC performance aspects.

| SB Integration Score Related to the Main SC Performance Aspects | The Edge, Amsterdam, The Netherlands | One Angel Square, Manchester, United Kingdom | National University of Singapore, Singapore | Ongos Valley Windhoek, Namibia | Reliance MET City, Gurgaon, India |
|---|---|---|---|---|---|
| Efficiency | 87.23% | 55.32% | 61.70% | 76.60% | 68.09% |
| Resilience | 85.00% | 55.00% | 67.50% | 80.00% | 67.50% |
| Environmental Sustainability | 87.18% | 56.41% | 66.67% | 74.36% | 71.79% |

Singapore, located in Asia, distinguishes itself by its extensive smart water management programs, which prioritize the significance of effective water utilization in an environment facing water scarcity. Conversely, Singapore's SC initiative seeks to revolutionize the city-state using technology, with a specific emphasis on enhancing the quality of life, developing cutting-edge infrastructure, ensuring fast connection, and demonstrating a strong dedication to sustainability and creativity [49,128]. The National University of Singapore embraces this ambition by incorporating intelligent technologies to better its campus and operations [129]. The total integration score is 63.34%, indicating a significant dedication to intelligent integration. The institution contributed significantly to 61.70% of the efficiency score (Table 6). This indicates that the SB services implemented at the NUS are effectively contributing to the efficient use of resources. This includes energy storage, smart heating, cooling, hot water preparation, and smart EV charging, all of which support campus efficiency. NUS also demonstrates a strong capacity to maintain critical operations and recover quickly from any breakdowns, achieving a 67.50% integration performance for resilience. This is supported by smart water monitoring and shut-off services to prevent leaks, and smart fire management to enhance buildings' safety and resilience. This enables the city to plan and respond effectively to security incidents, including implementation procedures to reduce and minimize the impact of such incidents. The university reflects a commitment to environmental stewardship and sustainable practices. This is evident in its implementing of renewable energy sources, smart water metering, and rainwater recycling, which all contribute to the campus' impact on the SC environmental sustainability score of 66.67%. NUS has made significant strides in integrating SB services, particularly in waste management, where it shows the ideal score, as illustrated in Figure 8. However, there are notable gaps in energy, mobility, water, and security domains. To reach the ideal integration levels, NUS could focus on adopting more comprehensive and advanced smart technologies and practices in these areas. Enhancing these domains would improve the performance and sustainability of NUS and contribute to its overall smart city objectives.

Windhoek, the capital city of Namibia, is formulating an SC concept that encompasses sustainability, enhanced resource management, and an elevated standard of living for its inhabitants. Ongos Valley is a project that seeks to support this goal by integrating intelligent technology into its infrastructure while prioritizing security. It adds to SC performance, notably city resilience [130,131]. The Ongos Valley has achieved a 77.60% integration score for efficiency, as shown in Table 6. This suggests that the SB services implemented effectively contribute to efficiently using resources, including energy storage, smart heating, cooling, hot water preparation, smart parking management, and smart EV charging. It also exhibits a robust ability to sustain essential activities and promptly bounce back from any disturbances, as seen by its resilience integration score of 80.00%. This is facilitated by smart water monitoring and shut-off services, smart fire management, and communication management during disaster events. In addition, the building's score of 74.36% in environmental sustainability integration shows a strong commitment to environmental protection and the implementation of sustainable practices. Adaptive sustainable energy sources, smart water metering, rainwater reuse, and the implementation of advanced waste management technologies such as smart bins and automated waste collection have contributed to reducing the impact on the environment. In conclusion, the Ongos Valley development achieved a 77.13% overall integration score, and demonstrated an exceptional score in integrating smart waste management and security services (Figure 8). Nevertheless, a significant disparity exists in energy, mobility, and water management. To achieve optimal levels of integration, Ongos Valley should prioritize the implementation of more extensive and sophisticated smart technologies and practices in these specific domains. By enhancing these domains, the impacts on SC performance efficiency and environmental sustainability of Ongos Valley would be improved and contribute to the wider objectives of establishing an environmentally sustainable and resilient urban environment in Windhoek.

Reliance MET City, also known as Model Economic Township, is a fully integrated industrial township in India. MET City is designed to be a self-sustained and eco-friendly township focusing on clean energy and waste management [132]. It includes industry clusters with support infrastructure of a logistics hub, rail and road connectivity, and social infrastructure including residential, commercial, recreational, and institutional development. The integration level is a measure of how well the various smart services are combined to function as a cohesive system [133]. According to Table 6, Reliance MET City has attained a commendable integration score of 68.09% for its integration impact on the SC's operational efficiency. This indicates that the established SB services successfully contribute to the efficient utilization of resources, including the monitoring and control of energy use, the intelligent regulation of heating, cooling, and hot water preparation, and intelligent electric vehicle charging. The impact on the city's resilience is reflected by a robust integration score of 67.50%, indicating its ability to effectively sustain essential functions and promptly bounce back from disturbances. This is facilitated by smart water monitoring and shut-off services, smart fire management, smart security lights, and an integrated sensor solution. The impact on the SC environmental sustainability performance is shown by MET City's impressive integration score of 71.79%, indicating a strong dedication to environmental care and sustainable practices. This is seen in the use of sustainable energy sources, smart water metering, greywater recycling, and supporting waste management services, all of which help mitigate the city's environmental sustainability. The results in Table 6 indicate that MET City, with a total integration of 67.15%, is making significant progress towards SC integration. Figure 8 indicates that it has most effectively integrated into waste management infrastructure, where it matches the ideal SB model score. However, there are notable gaps in the energy, mobility, water, and security domains. Reliance MET City could focus on adopting more comprehensive and advanced smart technologies and practices in these areas.

Summarizing the SB integration in SC evaluation results for the selected case studies, we can state that The Edge in Amsterdam distinguishes itself with outstanding integration scores, notably in the areas of energy, water, and security, closely aligning with or attaining the ideal scenario. These results complement the previous research by Apanaviciene et al. [30,32] and Al-Rimowicz and Nadler [31], placing the case of SB Edge in the SC of Amsterdam into the leading position over the other selected case studies. Ongos Valley demonstrates exceptional performance, particularly in the domains of waste management and security. NUS, One Angel Square, and Reliance MET City exhibit notable levels of integration, although they still have differing degrees of deficiencies compared to the ideal model. These gaps highlight the potential benefits of further integrating smart services. The performance of each case study is a direct reflection of how well it aligns with the aims of a smart city and its ability to utilize smart technology to improve urban infrastructure and services.

However, the evaluation results also highlight areas that need further development. For instance, there are opportunities for more integration in areas such as mobility and waste management. Moreover, certain SBs require improvements in specific domains such as energy and water management in order to fully achieve their SC goals. These findings suggest that more research and development should be conducted in the field of AI-powered evaluation tools for the integration of SBs. The focus of this study should be on areas that require improvement. Additional empirical research demonstrating practical applications of sophisticated artificial intelligence technologies in assessing the integration of SBs would be advantageous. Obtaining further information on their efficacy and obstacles will enhance understanding and aid in the formulation of plans for the development of a supply chain and sustainable business integration.

### *4.3. Practical Implications of the Research Findings for Smart Building Integration into a Smart City*

Consistent with our study's goals of designing and validating a thorough evaluation framework, the results of this study offer significant insights into the integration of SBs into the SCs research field. With energy-related aspects exhibiting the biggest overall impact (32.67%), followed by water management (23.96%) and security (19.96%), our results emphasize the diverse implications of SB services across many SC infrastructure categories. These findings are in line with earlier research, including those of Al-Rimowicz and Nadler [31] and Apanavičienė et al. [32], which have underlined the vital role of energy management in smart city development. However, our study extends beyond addressing the role of ICT and digitalization development in SB's integration into SC [30] by offering a more detailed examination of particular SB services and how they affect SC performance. The AI-based evaluation framework offers a more integrated and adaptable approach to assess the performance of SB within SC compared with other methodologies' frameworks, which rely on standardized metrics and indicators to assess the SB performance. While these frameworks provide a structured approach, they may lack the flexibility to account for unique urban contexts, rapid technological changes, and challenges in data management.

From 55.54% (One Angel Square) to 86.75% (The Edge, Amsterdam), the case studies study found notable differences in integration scores. These variations highlight the complexity of SB integration and fit Domingos et al.'s [29] claim that a consistent approach to both the design and evaluation of SBs inside the larger smart city environment is very essential. Our paradigm offers a consistent approach for evaluating integration across several domains, therefore meeting this demand.

The ramifications for practice and policy are significant. This paradigm helps urban designers and legislators prioritize expenditures on certain SB technologies with the best influence on general SC performance. For example, the great influence of energy-related elements implies that laws supporting the acceptance of smart energy management systems in buildings might greatly improve city-wide sustainability and efficiency. Moreover, the framework's capacity to spot areas of integration, as shown in the case studies, helps direct focused enhancements in particular fields. This corresponds with the suggestions of Rodríguez et al. [72] for using techniques and analysis tools supporting sustainable urban planning and general urban resilience.

Our results provide a road map for practitioners, especially building developers and operators, who seek to maximize interaction with SC infrastructure. The thorough analysis of impacts across efficiency, resilience, and environmental sustainability provides a complex outline of how various SB services support general SC performance, thereby guiding better-educated building design and operation.

Finally, this investigation not only presents an evaluation system that can serve as a decision-making tool to improve SB incorporation into SCs. To successfully accomplish long-term smart city objectives, stakeholders may analyze progress, identify performance gaps, and adjust strategies as necessary, with the help of the framework, which also offers a useful tool for the continual monitoring and benchmarking of smart city efforts. Future research should concentrate on longitudinal studies to evaluate the long-term effects of SB integration and investigate the possibilities of developing technologies to optimize this integration; for instance, this can be achieved by integrating the stochastic resource allocation approach [134] with an AI-based evaluation model.

## 5. Conclusions

The paper presents a comprehensive evaluation framework to assess the impacts of SB services on SC performance that employs the functionalities of advanced AI tools, namely, the LLMS models of Google's Bard and OpenAI's ChatGPT-3.

The literature analysis reveals that the existing frameworks provide useful insights; however, their complexity, involving numerous categories and indicators, poses challenges for implementation. Furthermore, they have not been adequately improved to assess emerging technologies and dynamic aspects that might significantly impact the integration of SBs over time. The authors of these frameworks also highlight the need for more research and growth in this field.

The recent literature on advanced AI applications, particularly ML and NLP, demonstrates their ability to improve the operational performance of both SBs and smart cities, to increase users' satisfaction and safety by optimizing energy consumption, enhance human–building interactions, and facilitate intelligent decision-making. This enables smooth communication between humans and machines, which is an important factor in managing SB services and smart city infrastructure. Recently developed Large Language Models like ChatGPT-3 and Bard expand the capabilities of artificial intelligence by producing language that resembles human writing and processing vast amounts of data, which is crucial for urban planning and emergency response systems. LLMs like Google Bard and ChatGPT-3 have proven their capacity for Sentiment Analysis by identifying patterns and trends that traditional methods may not have.

The AI-based methodology used for the evaluation of SB integration into SCs provided significant findings relevant to the assessment and further improvement of the performance of SCs. The proposed approach developed by the authors includes, first, an evaluation of the impacts of 26 factors related to SB services on the efficiency, resilience, and environmental sustainability of SC performance, and second, an assessment of the importance of all five infrastructure domains of SC. This process was conducted by utilizing advanced LLMs as AI experts, validated by human experts through two rounds of the Delphi technique. This allows for a more comprehensive assessment of factors contributing to the integration of SB into SC. The methodology applied provides a comprehensive and robust framework for the assessment of SB integration into SC. As a result, the priority of SB services related to smart city infrastructure domains was identified as follows: SB factors related to the smart energy domain had an impact of 32.67% on overall SC performance, while SB factors related to smart water management contributed 23.96%, SB factors related to smart security contributed 19.96%, SB factors related to smart mobility contributed 17.42%, and SB factors related to smart waste management contributed 5.99%.

The framework has been applied to case studies to analyze and reveal how SB services correspond with SC aims, in terms of efficiency, resilience, and environmental sustainability. The results of case studies emphasize the transformational potential of SBs in improving the performance of smart cities in smart energy, smart water management and smart security domains. However, the analysis of the results has also highlighted areas that need further integration development, such as mobility and waste management, to fully achieve the objectives of SC performance. Additional research should prioritize the expansion of the framework's application to a wider range of SB initiatives. This, in turn, would enhance the ability to make informed decisions on infrastructure development, resource allocation, and sustainability measures.

The presented research approach has demonstrated the capabilities of a very new AI tool application. The LLMs Google Bard and ChatGPT-3 have been recently developed, and it will take time to prove their applicability for research purposes. The Delphi technique enabled the effective validation of the evaluation framework for SB integration into the smart city, since experts achieved a significant level of consensus. The iterative process inspires future research by integrating significant observations and suggestions from industry professionals. The investigation revealed that while there was general agreement on most of the features of SBs, there are certain domains, such as mobility and security, that require further research and development in order to reach full expert consensus.

The main limitation of the proposed evaluation framework is that the current study implemented advanced AI tools to evaluate the SB services factors related to SC performance, as well as the importance of their SC domain, focusing mainly on the technological features of integrating SBs into smart cities. Non-technological aspects might be an important field for further investigation. Human factors, long-term sustainability capacity, user acceptance, and the cost-effectiveness of integrated solutions are important factors to consider in relation to the successful implementation of SB integration projects. Furthermore, future research could explore the potential of other AI tools and methods, specifically different machine learning algorithms, to automate the evaluation procedure. Also, incorporating stochastic modeling to address uncertainties in AI predictions and decision-making processes could significantly enhance the robustness of the AI-based framework for smart city planning. This will lead to the development of more advanced tools to evaluate the integration of SB into SC, and contribute to the dynamic development of a sustainable, resilient, and efficient urban environment.

**Supplementary Materials:** The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su16188032/s1, ChatGPT-3 prompt.

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## References

1. Dai, Y.; Hasanefendic, S.; Bossink, B. A systematic literature review of the smart city transformation process: The role and interaction of stakeholders and technology. *Sustain. Cities Soc.* **2024**, *101*, 105112. [CrossRef]
2. Nahiduzzaman, K.M.; Holland, M.; Sikder, S.K.; Shaw, P.; Hewage, K.; Sadiq, R. Urban Transformation Toward a Smart City: An E-Commerce-Induced Path-Dependent Analysis. *J. Urban Plan. Dev.* **2021**, *147*, 04020060. [CrossRef]
3. Giffinger, R.; Fertner, C.; Kramar, H.; Kalasek, R.; Milanović, N.; Meijers, E. Smart cities-Ranking of European medium-sized cities. *Rapp. Tech. Vienna Cent. Reg. Sci.* **2007**. [CrossRef]
4. Leroux, E.; Pupion, P.C. Smart territories and IoT adoption by local authorities: A question of trust, efficiency, and relationship with the citizen-user-taxpayer. *Technol. Forecast. Soc. Chang.* **2022**, *174*, 121195. [CrossRef]
5. Apanavičienė, R.; Shahrabani, M.M.N. Key Factors Affecting Smart Building Integration into Smart City: Technological Aspects. *Smart Cities* **2023**, *6*, 1832–1857. [CrossRef]
6. Syed, A.S.; Sierra-Sosa, D.; Kumar, A.; Elmaghraby, A. IoT in Smart Cities: A Survey of Technologies, Practices and Challenges. *Smart Cities* **2021**, *4*, 429–475. [CrossRef]
7. Ahad, M.A.; Paiva, S.; Tripathi, G.; Feroz, N. Enabling technologies and sustainable smart cities. *Sustain. Cities Soc.* **2020**, *61*, 102301. [CrossRef]
8. Alahi, M.E.E.; Sukkuea, A.; Tina, F.W.; Nag, A.; Kurdthongmee, W.; Suwannarat, K.; Mukhopadhyay, S.C. Integration of IoT-Enabled Technologies and Artificial Intelligence (AI) for Smart City Scenario: Recent Advancements and Future Trends. *Sensors* **2023**, *23*, 5206. [CrossRef]
9. Nguyen, H.; Nawara, D.; Kashef, R. Connecting the indispensable roles of IoT and artificial intelligence in smart cities: A survey. *J. Inf. Intell.* **2024**, *2*, 261–285. [CrossRef]
10. Caragliu, A.; Del Bo, C.; Nijkamp, P. Smart Cities in Europe. *J. Urban Technol.* **2011**, *18*, 65–82. [CrossRef]

11. Mullick, M.; Patnaik, A. Pandemic Management, Citizens and the Indian Smart Cities: Reflections from the Right to the Smart City and the Digital Divide. *City Cult. Soc.* **2022**, *30*, 100474. [CrossRef]
12. Sharif, A.A.R. Holistic Smart City Risk Assessment Framework. 2024 June. Available online: http://qspace.qu.edu.qa/handle/10576/56443 (accessed on 18 July 2024).
13. Froufe, M.M.; Chinelli, C.K.; Guedes, A.L.A.; Haddad, A.N.; Hammad, A.W.A.; Soares, C.A.P. Smart Buildings: Systems and Drivers. *Buildings* **2020**, *10*, 153. [CrossRef]
14. Hui, T.K.L.; Sherratt, R.S.; Sánchez, D.D. Major requirements for building Smart Homes in Smart Cities based on Internet of Things technologies. *Future Gener Comput. Syst.* **2017**, *76*, 358–369. [CrossRef]
15. Smart Readiness Indicator-European Commission. Available online: https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficient-buildings/smart-readiness-indicator_en (accessed on 25 July 2024).
16. UL Solutions. Spiretm Qualification Program. Available online: https://www.ul.com/services/spire-qualification-program (accessed on 25 July 2024).
17. Level(s): A Guide to Europe's New Reporting Framework for Sustainable Buildings. European Commission; 2018 Apr. Available online: https://apo.org.au/node/212906 (accessed on 25 July 2024).
18. English-BREEAM-NL. Available online: https://www.breeam.nl/english-9 (accessed on 25 July 2024).
19. LEED Rating System | U.S. Green Building Council. Available online: https://www.usgbc.org/leed (accessed on 25 July 2024).
20. GmbH, D. DGNB GmbH. German Sustainable Building Council. Available online: https://www.dgnb.de/en (accessed on 25 July 2024).
21. Derrible, S.; Cheah, L.; Arora, M.; Yeow, L.W. Urban Metabolism. In *Urban Informatics*; Shi, W., Goodchild, M.F., Batty, M., Kwan, M.P., Zhang, A., Eds.; Springer: Singapore, 2021; pp. 85–114. [CrossRef]
22. European Green Capital Award-European Commission. Available online: https://environment.ec.europa.eu/topics/urban-environment/european-green-capital-award_en (accessed on 18 July 2024).
23. European Cities SDG Index. 2019. Available online: https://euro-cities.sdgindex.org/#/ (accessed on 26 July 2024).
24. Mega, V.; Pedersen, J. *Urban Sustainability Indicators*; European Foundation for the Improvement of Living and Working Conditions: Luxembourg, 1998; 38p. Available online: https://www.eurofound.europa.eu/en/publications/2012/urban-sustainability-indicators/ (accessed on 26 July 2024).
25. Smart City Index 2021. Available online: https://imd.cld.bz/Smart-City-Index-2021/4/ (accessed on 26 July 2024).
26. RFSC. Reference Framework for Sustainable Cities. Available online: http://rfsc.eu/ (accessed on 26 July 2024).
27. United for Smart Sustainable Cities (U4SSC)–United for Smart Sustainable Cities (U4SSC). Available online: https://u4ssc.itu.int/ (accessed on 26 July 2024).
28. IESE Cities in Motion Index 2020-Cities in Motion. 2020. Available online: https://blog.iese.edu/cities-challenges-and-management/2020/10/27/iese-cities-in-motion-index-2020/ (accessed on 26 July 2024).
29. Domingos, L.; Sousa, M.J.; Resende, R.; Miranda, B.P.; Rego, S.; Ferreira, R. Establishment of a Smart Building Assessment Framework in the Context of Smart Cities | Emerald Insight. 2024 May. Available online: https://www.emerald.com/insight/content/doi/10.1108/BEPAM-07-2023-0116/full/html?casa_token=SoE2zt96E-0AAAAA:MvHY1mFPhhHJ5Kyc0oOAzR0PR8Zh1v42GOnQq8yXKbliLgwLEwceWetDQO6Qg9RMp_hhr2w2mtnn64tqERAPo9b8xfxQTo-Ny29cYjg4ZpP9QK4cBTc (accessed on 17 July 2024).
30. Apanaviciene, R.; Vanagas, A.; Fokaides, P. Smart Building Integration into a Smart City (SBISC): Development of a New Evaluation Framework. *Energies* **2020**, *13*, 2190. [CrossRef]
31. Al-Rimawi, T.H.; Nadler, M. Evaluating Cities and Real Estate Smartness and Integration: Introducing a Comprehensive Evaluation Framework. *Sustainability* **2023**, *15*, 9518. [CrossRef]
32. Apanaviciene, R.; Urbonas, R.; Fokaides, P.A. Smart Building Integration into a Smart City: Comparative Study of Real Estate Development. *Sustainability* **2020**, *12*, 9376. [CrossRef]
33. Chan, B. IIoT World. 2020. Smart Buildings–What's the Value to Smart Cities? Part Two. Available online: https://www.iiot-world.com/smart-cities-buildings-infrastructure/smart-buildings/smart-buildings-whats-the-value-to-smart-cities-part-two/ (accessed on 10 June 2023).
34. European Court of Auditors. Special Report 24/2023: Smart Cities. Available online: http://www.eca.europa.eu/en/publications/sr-2023-24 (accessed on 18 July 2024).
35. Brant, J. How Smart Buildings are Making an Impact on Smart Cities | LinkedIn. 2023. Available online: https://www.linkedin.com/pulse/how-smart-buildings-making-impact-cities-jess-brant/ (accessed on 19 July 2024).
36. Winkowska, J.; Szpilko, D. Methodology for Integration of Smart City Dimensions in the Socialised Process of Creating City Development. *Eur. Res. Stud.* **2020**, *23*, 524–547. [CrossRef]
37. Baharetha, S.; Soliman, A.M.; Hassanain, M.A.; Alshibani, A.; Ezz, M.S. Assessment of the Challenges Influencing the Adoption of Smart Building Technologies. *Front. Built Environ.* **2024**, *9*, 1334005. [CrossRef]
38. Khan, W.; Daud, A.; Khan, K.; Muhammad, S.; Haq, R. Exploring the frontiers of deep learning and natural language processing: A comprehensive overview of key challenges and emerging trends. *Nat. Lang. Process J.* **2023**, *4*, 100026. [CrossRef]
39. Ray, P.P. ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope. *Internet Things Cyber-Phys. Syst.* **2023**, *3*, 121–154. [CrossRef]

40. Zuheros, C.; Martínez-Cámara, E.; Herrera-Viedma, E.; Katib, I.A.; Herrera, F. Explainable Crowd Decision Making methodology guided by expert natural language opinions based on Sentiment Analysis with Attention-based Deep Learning and Subgroup Discovery. *Inf. Fusion* **2023**, *97*, 101821. [CrossRef]
41. Su, J.; Jiang, C.; Jin, X.; Qiao, Y.; Xiao, T.; Ma, H.; Wei, R.; Jing, Z.; Xu, J.; Lin, J. Large Language Models for Forecasting and Anomaly Detection: A Systematic Literature Review. *arXiv* **2024**, arXiv:2402.10350.
42. Malekpour Koupaei, D.; Song, T.; Cetin, K.S.; Im, J. An assessment of opinions and perceptions of smart thermostats using aspect-based sentiment analysis of online reviews. *Build. Environ.* **2020**, *170*, 106603. [CrossRef]
43. Alanne, K.; Sierla, S. An overview of machine learning applications for smart buildings. *Sustain. Cities Soc.* **2022**, *76*, 103445. [CrossRef]
44. Panchalingam, R.; Chan, K.C. A state-of-the-art review on artificial intelligence for Smart Buildings. *Intell. Build. Int.* **2021**, *13*, 203–226. [CrossRef]
45. Hadi, M.U.; Tashi, Q.A.; Qureshi, R.; Shah, A.; Muneer, A.; Irfan, M.; Zafar, A.; Shaikh, M.B.; Akhtar, N.; Wu, J.; et al. A Survey on Large Language Models: Applications, Challenges, Limitations, and Practical Usage. 2023 Jul. Available online: https://www.techrxiv.org/doi/full/10.36227/techrxiv.23589741.v1 (accessed on 25 February 2024).
46. Ali, A.; Jayaraman, R.; Azar, E.; Maalouf, M. A comparative analysis of machine learning and statistical methods for evaluating building performance: A systematic review and future benchmarking framework. *Build. Environ.* **2024**, *252*, 111268. [CrossRef]
47. Shahrabani, M.M.N.; Apanavičienė, R. Towards integration of smart and resilient city: Literature review. *IOP Conf. Ser. Earth Environ. Sci.* **2022**, *1122*, 012019. [CrossRef]
48. Singh, T.; Solanki, A.; Sharma, S. Role of Smart Buildings in Smart City—Components, Technology, Indicators, Challenges, Future Research Opportunities. In Digital Cities Roadmap: IoT-Based Architecture and Sustainable Buildings; Scrivener Publisher; Beverly, MA, USA, 2021; pp. 449–476.
49. Al Dakheel, J.; Del Pero, C.; Aste, N.; Leonforte, F. Smart buildings features and key performance indicators: A review. *Sustain. Cities Soc.* **2020**, *61*, 102328. [CrossRef]
50. Roccotelli, M.; Mangini, A.M. Advances on Smart Cities and Smart Buildings. *Appl. Sci.* **2022**, *12*, 631. [CrossRef]
51. Affonso, E.O.T.; Branco, R.R.; Menezes, O.V.C.; Guedes, A.L.A.; Chinelli, C.K.; Haddad, A.N.; Soares, C.A.P. The Main Barriers Limiting the Development of Smart Buildings. *Buildings* **2024**, *14*, 1726. [CrossRef]
52. Kozlowski, W.; Suwar, K. Smart City: Definitions, Dimensions, and Initiatives. *Eur. Res. Stud.* **2021**, *XXIV*, 509–520. [CrossRef]
53. El-Motasem, S.; Khodeir, L.M.; Fathy Eid, A. Analysis of challenges facing smart buildings projects in Egypt. *Ain. Shams Eng. J.* **2021**, *12*, 3317–3329. [CrossRef]
54. Alohan, E.O.; Oyetunji, A.K.; Amaechi, C.V.; Dike, E.C.; Chima, P. An Agreement Analysis on the Perception of Property Stakeholders for the Acceptability of Smart Buildings in the Nigerian Built Environment. *Buildings* **2023**, *13*, 1620. [CrossRef]
55. Ghaffarianhoseini, A.; Berardi, U.; AlWaer, H.; Chang, S.; Halawa, E.; Ghaffarianhoseini, A.; Clements-Croome, D. What is an intelligent building? Analysis of recent interpretations from an international perspective. *Archit. Sci. Rev.* **2016**, *59*, 338–357. [CrossRef]
56. Radziejowska, A.; Sobotka, B. Analysis of the Social Aspect of Smart Cities Development for the Example of Smart Sustainable Buildings. *Energies* **2021**, *14*, 4330. [CrossRef]
57. Ghansah, F.A.; Owusu-Manu, D.G.; Ayarkwa, J. Project management processes in the adoption of smart building technologies: A systematic review of constraints. *Smart Sustain. Built Environ.* **2020**, *10*, 208–226. [CrossRef]
58. Ejidike, C.C.; Mewomo, M.C. Benefits of adopting smart building technologies in building construction of developing countries: Review of literature. *SN Appl. Sci.* **2023**, *5*, 52. [CrossRef]
59. Zhao, S.; Zhang, P.; Li, W. A Study on Evaluation of Influencing Factors for Sustainable Development of Smart Construction Enterprises: Case Study from China. *Buildings* **2021**, *11*, 221. [CrossRef]
60. Himeur, Y.; Sayed, A.N.; Alsalemi, A.; Bensaali, F.; Amira, A. Edge AI for Internet of Energy: Challenges and perspectives. *Internet Things* **2024**, *25*, 101035. [CrossRef]
61. Ullah, A.; Qi, G.; Hussain, S.; Ullah, I.; Ali, Z. The Role of LLMs in Sustainable Smart Cities: Applications, Challenges, and Future Directions. *arXiv* **2024**, arXiv:2402.14596.
62. Ferrara, E. Should ChatGPT be Biased? Challenges and Risks of Bias in Large Language Models. First Monday. 7 November 2023. Available online: http://arxiv.org/abs/2304.03738 (accessed on 18 July 2024).
63. Wolniak, R.; Stecuła, K. Artificial Intelligence in Smart Cities—Applications, Barriers, and Future Directions: A Review. *Smart Cities* **2024**, *7*, 1346–1389. [CrossRef]
64. Bernstein, R. Integrated Systems: An End User Perspective. Available online: https://heinonline.org/HOL/LandingPage?handle=hein.journals/bclr55&div=41&id=&page= (accessed on 26 July 2024).
65. Sodhro, A.; Pirbhulal, S.; Luo, Z.; De Albuquerque, V.H.C. Towards an Optimal Resource Management for IoT based Green and Sustainable Smart Cities. *J. Clean. Prod.* **2019**, *220*, 1167–1179. [CrossRef]
66. Park, S.; Lee, S.; Park, S.; Park, S. AI-Based Physical and Virtual Platform with 5-Layered Architecture for Sustainable Smart Energy City Development. *Sustainability* **2019**, *11*, 4479. [CrossRef]
67. Sustainable Finance: TEG Final Report on the EU Taxonomy | Knowledge for Policy. Available online: https://knowledge4policy.ec.europa.eu/publication/sustainable-finance-teg-final-report-eu-taxonomy_en (accessed on 26 July 2024).

68. Sharifi, A. A global dataset on tools, frameworks, and indicator sets for smart city assessment. *Data Brief* **2020**, *29*, 105364. [CrossRef]
69. Implementing Data-Driven Smart City Applications for Future Cities. *Smart Cities* **2022**, *5*, 455–474. [CrossRef]
70. Jain, K. *Development of a Smart Building Evaluation System for Office Buildings*; Technische Universitat Berlin: Berlin, Germany, 2019.
71. Ullah, F.; Sepasgozar, S.M.E.; Wang, C. A Systematic Review of Smart Real Estate Technology: Drivers of, and Barriers to, the Use of Digital Disruptive Technologies and Online Platforms. *Sustainability* **2018**, *10*, 3142. [CrossRef]
72. Rodríguez, C.; Sanz-Montalvillo, C.; Vallejo, E.; Quijano, A. City-Level Evaluation: Categories, Application Fields and Indicators for Advanced Planning Processes for Urban Transformation. In *Smart and Sustainable Planning for Cities and Regions: Results of SSPCR 2019*; Bisello, A., Vettorato, D., Haarstad, H., Borsboom-van Beurden, J., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 17–35. [CrossRef]
73. Jia, M.; Komeily, A.; Wang, Y.; Srinivasan, R.S. Adopting Internet of Things for the development of smart buildings: A review of enabling technologies and applications. *Autom. Constr.* **2019**, *101*, 111–126. [CrossRef]
74. Baduge, S.K.; Thilakarathna, S.; Perera, J.S.; Arashpour, M.; Sharafi, P.; Teodosio, B.; Shringi, A.; Mendis, P. Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. *Autom. Constr.* **2022**, *141*, 104440. [CrossRef]
75. Farzaneh, H.; Malehmirchegini, L.; Bejan, A.; Afolabi, T.; Mulumba, A.; Daka, P.P. Artificial Intelligence Evolution in Smart Buildings for Energy Efficiency. *Appl. Sci.* **2021**, *11*, 763. [CrossRef]
76. Ullah, Z.; Al-Turjman, F.; Mostarda, L.; Gagliardi, R. Applications of Artificial Intelligence and Machine learning in smart cities. *Comput. Commun.* **2020**, *154*, 313–323. [CrossRef]
77. Ali, D.M.T.E.; Motuzienė, V.; Džiugaitė-Tumėnienė, R. AI-Driven Innovations in Building Energy Management Systems: A Review of Potential Applications and Energy Savings. *Energies* **2024**, *17*, 4277. [CrossRef]
78. Sarker, I.H. AI-Based Modeling: Techniques, Applications and Research Issues towards Automation, Intelligent and Smart Systems. *SN Comput. Sci.* **2022**, *3*, 158. [CrossRef] [PubMed]
79. Merabet, G.H.; Essaaidi, M.; Ben Haddou, M.; Qolomany, B.; Qadir, J.; Anan, M.; Al-Fuqaha, A.; Abid, M.R.; Benhaddou, D. Intelligent building control systems for thermal comfort and energy-efficiency: A systematic review of artificial intelligence-assisted techniques. *Renew. Sustain. Energy Rev.* **2021**, *144*, 110969. [CrossRef]
80. Estebsari, A.; Rajabi, R. Single Residential Load Forecasting Using Deep Learning and Image Encoding Techniques. *Electronics* **2020**, *9*, 68. [CrossRef]
81. Inclezan, D.; Pradanos, L.I. Viewpoint: A Critical View on Smart Cities and AI. *J. Artif. Intell. Res.* **2017**, *60*, 681–686. [CrossRef]
82. Gomaa, I.; Adelzadeh, M.; Gwynne, S.; Spencer, B.; Ko, Y.; Bénichou, N.; Ma, C.; Elsagan, N.; Duong, D.; Zalok, E.; et al. A Framework for Intelligent Fire Detection and Evacuation System. *Fire Technol.* **2021**, *57*, 3179–3185. [CrossRef]
83. Mohammadiounotikandi, A.; Fakhruldeen, H.F.; Meqdad, M.N.; Fareed, B.; Navimipour, N.; Unal, M. A Fire Evacuation and Control System in Smart Buildings Based on the Internet of Things and a Hybrid Intelligent Algorithm Evacuation and Control System in Smart Buildings Based on the Internet of Things and a Hybrid. *Fire* **2023**, *6*, 171. [CrossRef]
84. Asha, P.; Natrayan, L.; Geetha, B.T.; Beulah, J.R.; Sumathy, R.; Varalakshmi, G.; Neelakandan, S. IoT enabled environmental toxicology for air pollution monitoring using AI techniques. *Environ. Res.* **2022**, *205*, 112574. [CrossRef]
85. Wu, C.; Li, X.; Guo, Y.; Wang, J.; Ren, Z.; Wang, M.; Yang, Z. Natural language processing for smart construction: Current status and future directions. *Autom. Constr.* **2022**, *134*, 104059. [CrossRef]
86. Khurana, D.; Koli, A.; Khatter, K.; Singh, S. Natural language processing: State of the art, current trends and challenges. *Multimed Tools Appl.* **2023**, *82*, 3713–3744. [CrossRef]
87. Tyagi, N.; Bhushan, B. Demystifying the Role of Natural Language Processing (NLP) in Smart City Applications: Background, Motivation, Recent Advances, and Future Research Directions. *Wirel. Pers. Commun.* **2023**, *130*, 857–908. [CrossRef] [PubMed]
88. Kim, H.; Kang, H.; Choi, H.; Jung, D.; Hong, T. Human-building interaction for indoor environmental control: Evolution of technology and future prospects. *Autom. Constr.* **2023**, *152*, 104938. [CrossRef]
89. Genkin, M.; McArthur, J.J. B-SMART: A reference architecture for artificially intelligent autonomic smart buildings. *Eng. Appl. Artif. Intell.* **2023**, *121*, 106063. [CrossRef]
90. Senthilkumar, R. Speech Based Controlled Techniques Using Nlp. *J. Sci. Technol. Res. JSTAR* **2021**, *2*, 24–32.
91. Dong, L.; Liu, Y. Frontiers of Policy and Governance Research in a Smart City and Artificial Intelligence: An Advanced Review Based on Natural Language Processing. *Front. Sustain. Cities* **2023**, *5*, 1199041. [CrossRef]
92. Nicolas, C.; Kim, J.; Chi, S. Natural language processing-based characterization of top-down communication in smart cities for enhancing citizen alignment. *Sustain. Cities Soc.* **2021**, *66*, 102674. [CrossRef]
93. de Oliveira, N.R.; Lúcio Reis, H.A.; Fernandes, N.C.; Carlos Bastos, A.M.; Dianne Medeiros, S.V.; Diogo Mattos, M.F. Natural Language Processing Characterization of Recurring Calls in Public Security Services. In Proceedings of the International Conference on Computing, Networking and Communications (ICNC), Big Island, HI, USA, 17–20 February 2020; pp. 1009–1013.
94. Yang, T.; Xie, J.; Li, G.; Mou, N.; Chen, C.; Zhao, J.; Liu, Z.; Lin, Z. Traffic Impact Area Detection and Spatiotemporal Influence Assessment for Disaster Reduction Based on Social Media: A Case Study of the 2018 Beijing Rainstorm. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 136. [CrossRef]
95. Zhang, Y.; Chen, Z.; Zheng, X.; Chen, N.; Wang, Y. Extracting the location of flooding events in urban systems and analyzing the semantic risk using social sensing data. *J. Hydrol.* **2021**, *603*, 127053. [CrossRef]

96. Chung, S.; Moon, S.; Kim, J.; Kim, J.; Lim, S.; Chi, S. Comparing natural language processing (NLP) applications in construction and computer science using preferred reporting items for systematic reviews (PRISMA). *Autom. Constr.* **2023**, *154*, 105020. [CrossRef]
97. Hadi, M.U.; Tashi, Q.A.; Qureshi, R.; Shah, A.; Muneer, A.; Irfan, M.; Zafar, A.; Shaikh, M.B.; Akhtar, N.; Wu, J.; et al. Large Language Models: A Comprehensive Survey of its Applications, Challenges, Limitations, and Future Prospects. 2023 Nov. Available online: https://www.techrxiv.org/doi/full/10.36227/techrxiv.23589741.v4 (accessed on 19 February 2024).
98. Akhtar, M.; Moridpour, S. A Review of Traffic Congestion Prediction Using Artificial Intelligence. *J. Adv. Transp.* **2021**, *2021*, e8878011. [CrossRef]
99. Li, Z.; Ma, J.; Tan, Y.; Guo, C.; Li, X. Combining physical approaches with deep learning techniques for urban building energy modeling: A comprehensive review and future research prospects. *Build. Environ.* **2023**, *246*, 110960. [CrossRef]
100. Shoaib, M.R.; Emara, H.M.; Zhao, J. A Survey on the Applications of Frontier AI, Foundation Models, and Large Language Models to Intelligent Transportation Systems. In Proceedings of the International Conference on Computer and Applications (ICCA), Cairo, Egypt, 28–30 November 2023; pp. 1–7.
101. Kalyan, K.S. A survey of GPT-3 Family Large Language Models Including ChatGPT and GPT-4. *Nat. Lang. Process J.* **2024**, *6*, 100048. [CrossRef]
102. What Is a Large Language Model? | A Comprehensive LLMs Guide. Available online: https://www.elastic.co/what-is/large-language-models (accessed on 23 July 2024).
103. Muehmel, K. What Is a Large Language Model, the Tech Behind ChatGPT? *2024.* Available online: https://blog.dataiku.com/large-language-model-chatgpt (accessed on 26 July 2024).
104. Ahmed, I.; Kajol, M.A.; Hasan, U.; Datta, P.P.; Roy, A.; Reza, M.d.R. ChatGPT versus Bard: A comparative study. *Eng. Rep.* **2024**, e12890. [CrossRef]
105. Medhat, W.; Hassan, A.; Korashy, H. Sentiment analysis algorithms and applications: A survey. *Ain. Shams.Eng. J.* **2014**, *5*, 1093–1113. [CrossRef]
106. Editor, C. What Is Sentiment Analysis: LLMs Explained. Chatgptguide.ai. 2024. Available online: https://www.chatgptguide.ai/2024/03/03/what-is-sentiment-analysis-llms-explained/ (accessed on 22 July 2024).
107. Dhaduk, H. Deepchecks. OpenAI's ChatGPT vs. Google's Bard AI: A Comparative Analysis. 2023. Available online: https://deepchecks.com/openais-chatgpt-vs-googles-bard-ai-a-comparative-analysis/ (accessed on 21 July 2024).
108. Montti, R. Search Engine Journal. 2023. Google Bard AI-What Sites Were Used to Train It? Available online: https://www.searchenginejournal.com/google-bard-training-data/478941/ (accessed on 22 July 2024).
109. Yang, A.C. Addressing the Limitations of LLMs: Biases, Safety, Ethics, and Interpretability. Medium. 2023. Available online: https://medium.com/@platformai/addressing-the-limitations-of-llms-biases-safety-ethics-and-interpretability-4af65a876bb1 (accessed on 25 August 2024).
110. Mensah, G.B. Artificial Intelligence and Ethics: A Comprehensive Review of Bias Mitigation, Transparency, and Accountability in AI Systems. *arXiv* **2023**. Available online: https://www.researchgate.net/profile/George-Benneh-Mensah/publication/375744287_Artificial_Intelligence_and_Ethics_A_Comprehensive_Review_of_Bias_Mitigation_Transparency_and_Accountability_in_AI_Systems/links/656c8e46b86a1d521b2e2a16/Artificial-Intelligence-and-Ethics-A-Comprehensive-Review-of-Bias-Mitigation-Transparency-and-Accountability-in-AI-Systems.pdf (accessed on 20 August 2024).
111. Ferrara, E. Fairness and Bias in Artificial Intelligence: A Brief Survey of Sources, Impacts, and Mitigation Strategies. *Sci* **2024**, *6*, 3. [CrossRef]
112. Ding, B.; Li, Z.; Li, Z.; Xue, Y.; Chang, X.; Su, J.; Jin, X.; Sun, H. A CCP-based distributed cooperative operation strategy for multi-agent energy systems integrated with wind, solar, and buildings. *Appl. Energy* **2024**, *365*, 123275. [CrossRef]
113. Waisberg, E.; Ong, J.; Masalkhi, M.; Zaman, N.; Sarker, P.; Lee, A.G.; Tavakkoli, A. Google's AI chatbot "Bard": A side-by-side comparison with ChatGPT and its utilization in ophthalmology. *Eye* **2023**, *38*, 642–645. [CrossRef]
114. Anindya. Medium. Google Bard and OpenAI: How Do These AI Powerhouses Measure up? 2023. Available online: https://bootcamp.uxdesign.cc/google-bard-and-openai-how-do-these-ai-powerhouses-measure-up-978caf993432 (accessed on 14 December 2023).
115. Google. Try Bard and Share Your Feedback. 2023. Available online: https://blog.google/technology/ai/try-bard/ (accessed on 14 December 2023).
116. Khennouche, F.; Elmir, Y.; Himeur, Y.; Djebari, N.; Amira, A. Revolutionizing generative pre-traineds: Insights and challenges in deploying ChatGPT and generative chatbots for FAQs. *Expert Syst. Appl.* **2024**, *246*, 123224. [CrossRef]
117. Korkmaz, A.; Aktürk, C.; Talan, T. Analyzing the User's Sentiments of ChatGPT Using Twitter Data. *Iraqi J. Comput. Sci. Math.* **2023**, *4*, 202–214. [CrossRef]
118. Liu, B. *Sentiment Analysis: Mining Opinions, Sentiments, and Emotions*; Computational Linguistics 42, No. 3: University of Illinois: Chicago, IL, USA, 2015; pp. 595–598. [CrossRef]
119. Turoff, M.; Linstone, H.A. The Delphi Method: Techniques and Applications. 1975. Available online: https://www.jstor.org/stable/3150755 (accessed on 24 July 2024).
120. Daraqel, B.; Wafaie, K.; Mohammed, H.; Cao, L.; Mheissen, S.; Liu, Y.; Zheng, L. The performance of Artificial Intelligence Models in Generating Responses to General Orthodontic Questions: ChatGPT vs Google Bard. *Am. J. Orthod. Dentofacial. Orthop.* **2024**, *1635*, 652–662. [CrossRef] [PubMed]

121. Barrios, M.; Guilera, G.; Nuño, L.; Gómez-Benito, J. Consensus in the delphi method: What makes a decision change? *Technol. Forecast. Soc. Chang.* **2020**, *163*, 120484. [CrossRef]
122. Clibbens, N.; Walters, S.; Baird, W. Delphi research: Issues raised by a pilot study. *Nurse Res.* **2012**, *19*, 37–44. [CrossRef] [PubMed]
123. Nesti, G. Defining and assessing the transformational nature of smart city governance: Insights from four European cases. *Int. Rev. Adm. Sci.* **2020**, *86*, 20–37. [CrossRef]
124. EDGE. EDGE | The Edge. Available online: https://edge.tech/portfolio/the-edge (accessed on 2 January 2024).
125. Design Life-Cycle. The Edge in Amsterdam. Available online: http://www.designlife-cycle.com/new-page-84 (accessed on 2 January 2024).
126. Collier, C.; The Manchester Model: How A City's Urban Past Influences Its Smart City Future. Smart Cities Connect. 2019. Available online: https://smartcitiesconnect.org/the-manchester-model-how-a-citys-urban-past-influences-its-smart-city-future/ (accessed on 2 January 2024).
127. ArchDaily. 2013. 1 Angel Square/3D Reid. Available online: https://www.archdaily.com/337430/1-angel-square-3d-reid (accessed on 2 January 2024).
128. IoMob BC Ph D CEO. Top 10 Blockchain Cities in the World: The Methodology. Medium. 2018. Available online: https://boydcohen.medium.com/top-10-blockchain-cities-in-the-world-the-methodology-8a96bbfb666d (accessed on 2 January 2024).
129. Dezeen. National University of Singapore Starts Building a Zero-Energy School. 2016. Available online: https://www.dezeen.com/2016/11/07/national-university-singapore-building-zero-energy-design-school/ (accessed on 2 January 2024).
130. All You Need to Know About Ongos Valley | Property News Namibia. Available online: https://propertynews.com.na/latest-news/all-you-need-to-know-about-ongos-valley (accessed on 2 January 2024).
131. Ongos Valley-Your Own Home Starts Here. 2020. Available online: https://www.ongosvalley.com.na/ (accessed on 2 January 2024).
132. Gurgaon Apartments. Reliance MET City, Reliance MET City Residential Plots Price, Reliance MET Industrial Plots. Available online: https://www.gurgaonapartments.in/projects/reliance-met.html (accessed on 27 December 2023).
133. MET City-Meet Your Future Here | Growth Is Life. Available online: https://www.metcityplots.com/ (accessed on 27 December 2023).
134. Zhang, H.; Li, Z.; Xue, Y.; Chang, X.; Su, J.; Wang, P.; Guo, Q.; Sun, H. A Stochastic Bi-level Optimal Allocation Approach of Intelligent Buildings Considering Energy Storage Sharing Services. *IEEE Trans. Consum. Electron.* **2024**, 1–1. [CrossRef]