Challenges with the Integration of Smart City Technologies in a Small City: A Case Study for Stirling.

By

Nina Daraio
Student Number: 2917284

Dissertation Submitted in part fulfilment for the degree of
BSc (Hons) in Management

University of Stirling

April 2024

Acknowledgments

I extend my sincere gratitude to my supervisor, Gerry Edgar, for his continuous support and insightful advice, which were invaluable throughout the development of this dissertation.

Many thanks to my boyfriend, friends, and family for always being ready to lend a hand and for their unwavering presence and constant encouragement.

Thank you all for being part of this journey.

Table of Contents

Abstract

This research investigates the adoption of smart city technologies in Stirling, with a specific focus on the implementation and community acceptance of IoT-powered smart bins. Given the rise in smart urban development around the world, this study seeks to explore the unique context of Stirling, examining the feasibility, practicality, and societal implications of integrating advanced waste management solutions. Data was collected through a survey distributed among Stirling residents, the responses were quantitatively analysed to understand perceptions, willingness to adopt, and the potential social benefits or drawbacks of smart bins.

Findings reveal a general openness and positive attitude towards smart technology across various demographics, indicating a strong potential for Stirling to embrace smart city initiatives. However, a small survey sample size and rapid technological advancements pose limitations to the study's generalisability and future relevance. Ethical considerations, including participant privacy and the reasonable deployment of technology, were rigorously addressed, ensuring the study's integrity.

This research contributes to the discourse on smart cities by highlighting the opportunities and challenges of adopting smart technologies in smaller urban environments, offering insights for policymakers, urban planners, and stakeholders in similar settings. The study indicates Stirling is ready to adopt smart bins, with positive community response and perceived benefits outweighing concerns. Recommendations focus on education and inclusive technology deployment, aligned with the Technology Acceptance Model. These efforts aim to advance Stirling as a sustainable smart city, attentive to resident needs and ongoing stakeholder engagement.

List of Figures

1. Chapter 1 – Introduction to Research:

1.2 Research Background

The concept of Smart Cities, typically used when referring to densely populated metropolitan areas, highlights a notable research gap when it comes to smaller urban settings. This discrepancy brings the city of Stirling into focus, a community with a population of approximately 93,470 inhabitants according to the National Records of Scotland (NRS, 2021). Stirling offers a unique case to explore the adaptability and feasibility of integrating smart city technologies in smaller urban environments. The central research problem investigates into whether Stirling can realistically adopt smart city-like innovations, specifically targeting IoT-powered smart bins for this study. These technologies were selected based on their recognised potential benefits for the city. Although their introduction might be disruptive to the current waste management systems, this adoption would not create a lifestyle change to the residents. Implementing such technologies in Stirling may not immediately classify it as a smart city; however, it could be an important first step towards such a transformation.

The uncertainty surrounding the practicality of these smart solutions in Stirling underscores the research's significance. It's not just about the technological feasibility but also about understanding how these innovations can improve the quality of life in smaller towns, which often deal with resource constraints unlike their larger urban counterparts. The exploration into smart technologies such as smart bins, extend beyond their surface-level benefits of waste management efficiency and environmental sustainability. It investigates into the broader implications of how such technologies can create a more engaged and environmentally conscious community, promote economic development through innovative waste management solutions, and enhance the overall urban infrastructure in a manner that is both sustainable and scalable.

Moreover, this research aims to shed light on the adaptability of smart city concepts to smaller urban areas, considering the unique challenges and opportunities they present. It involves a detailed analysis of the potential costs and benefits, the societal readiness for such a transition, and the environmental impact. By examining these factors, the research seeks to provide a comprehensive understanding of the feasibility of implementing smart technologies in Stirling and similar urban settings.

Additionally, the investigation into Stirling's potential to adopt smart city technologies highlights a broader discussion on the scalability of such innovations. It prompts a re-evaluation of the smart city model, traditionally twisted towards larger cities, to encompass a more inclusive approach that considers the diverse urban landscapes across the globe. This perspective encourages a more rounded view of urban development, recognizing the value of smaller cities and towns as vital contributors to the global movement towards more sustainable and technologically integrated urban spaces.

The research on Stirling's potential to incorporate smart city-like technologies such as IoT powered smart bins is not just about the technological implementation but about reimagining the future of urban living in smaller communities. It challenges the conventional understanding of smart cities, advocating for a more flexible and inclusive approach that acknowledges the unique attributes and needs of smaller urban areas. With this approach, the study aims to contribute to the evolving discourse on smart cities, offering insights and strategies that are relevant, sustainable, and adaptable to the diverse urban ecosystems around the world.

1.2 Research Purpose

The goal of this research is to extend the boundaries of smart city studies by exploring the case of small towns. Stirling serves as an ideal backdrop for evaluating the transferability and scalability of smart technologies commonly associated with larger cities as they normally require a great amount of energy and resources *(Routray, Sarangi and Javali, 2021)*. This research aims not just to understand the feasibility and adaptability of implementing IoT-powered smart bins, but also to explore their projected societal and managerial implications, as well as contributing fresh perspectives to the academic discussion of smart cities.

1.3 Research Value

This study is positioned to make a substantial contribution to both the academic field and practical application, specifically by shifting the focus towards smaller urban environments. It aims to bridge a significant gap in the existing academic discourse on smart cities by expanding the scope and adaptability of smart city principles to less traditionally focused areas. Selecting Stirling as the focus of this study introduces a fresh perspective on the impact and feasibility of smart technologies in smaller settings, offering novel insights into their integration and utility. This investigation is particularly relevant for policymakers, local governments, and technology enterprises interested in the deployment of smart solutions in smaller communities, providing them with actionable insights and a roadmap for implementation. By analysing the effectiveness and sustainability of waste management strategies facilitated by smart technologies in Stirling, the research aims to offer practical solutions tailored to the unique challenges and opportunities of such urban areas. Ultimately, the study aims to deliver a well-rounded understanding of the scalability and adaptability of smart city technologies, illustrating how they can enhance urban living and environmental sustainability in smaller urban landscapes. This comprehensive approach not only contributes to academic knowledge but also serves as a practical guide for communities seeking to leverage smart technologies for improved urban management and quality of life.

1.4 Research Reliability and Validity

To ensure the reliability and validity of this study, a structured approach will be adopted, focusing on rigorous data collection and analysis methods. Reliability will be ensured through the application of consistent, standardized data collection techniques. This will include the deployment of a carefully designed questionnaire, inspired by the methodologies of Georgiadis et al. (2021) and Brown (2022), which have been recognized for their effectiveness in gathering accurate data. Furthermore, the study will leverage SPSS for data analysis, ensuring that the processing of data is both precise and reliable.

To reinforce the validity of the research, the design of the questionnaire will be closely aligned with the specific objectives of the study. This alignment is crucial for ensuring that the data collected directly contributes to addressing the research questions, a methodological principle similar to the work of Harrison and Donnelly (2011). By meticulously structuring the questionnaire and selecting appropriate statistical tools for analysis, this study aims to produce findings that are not only analytically correct but also relevant to the research objectives. This focus on quantitative methods emphasizes the importance of objective measurement and numerical analysis in validating the feasibility of smart city technologies in smaller urban settings like Stirling. Through this careful and structured approach, the study aspires to offer credible, valuable insights into the adoption of smart technologies, contributing to the discussion on smart urban development in smaller communities.

1.5 Research Aim and Objectives

The aim of this research is to assess the feasibility, adaptability, and community impact of implementing smart city technologies such as smart bins in the smaller urban context of Stirling.

In order to achieve this, the following research objectives have been identified:

RO 1: To outline what is meant by smart city and understand why this concept is mostly associated with large urban environments.

RO 2: To evaluate the practicality of implementing IoT powered Smart Bins in Stirling, considering the town's unique size, and demographics

RO 3: To measure the potential social benefits or drawbacks of introducing smart waste management systems, with a focus on quality of life.

RO 4: To collect and analyse input from various stakeholders such as residents, aiming to understand their views, needs, and concerns regarding the possible implementation of IoT powered smart bins as well as understanding how the responses fit into the TAM model .

RO 5: To synthesize findings into actionable recommendations for local government, and other stakeholders, outlining best practices and potential limitations.

1.6 Research Structure

This study begins with an introduction that highlights the research background, underscoring the importance of such technologies in smaller urban settings and outlining the study's aims, objectives, and overall structure to ensure robust and credible findings. Chapter 2 broadens the discussion by offering an overview of smart cities, emphasizing the significance of IoT-powered smart bins as a promising technological solution, and setting the stage for an in-depth analysis. The literature review explores the concept, historical development, and societal impact of smart cities, employing theoretical frameworks such as diffusion theory and the technology acceptance model which help to grasp societal perception. Chapter 4 explores the methodological approaches, describing the use of quantitative methods to investigate the study's research questions. This includes a thorough justification for the selection of specific tools and techniques, as well as an in-depth analysis of the ethical implications and limitations associated with the research.

Chapter 5 presents the findings from the data collection and analysis, crucial for understanding the practical implications of implementing smart technologies in Stirling. The discussion in Chapter 6 integrates these findings with the literature review to draw meaningful conclusions and offer an understanding of the study's implications. Concluding with Chapter 7, the study will summarise the key findings gathered and will suggest directions for future research. Through this structured examination and analysis, the study aims to provide valuable insights into the feasibility and desirability of smart city technologies in enhancing urban living in smaller communities, contributing to the broader discourse on sustainable urban development.

1.7 Why IoT Powered Smart Bins?

IoT-powered smart bins were chosen for this research as their possible implementation in Stirling as part of a strategic choice to address the evolving waste management and environmental sustainability needs of smaller urban environments. This decision is supported by the recognition of the unique advantages that smart technology brings to urban infrastructure, particularly in enhancing waste management systems. Firstly, smart bins directly contribute to more efficient waste collection processes by utilizing sensors to monitor fill levels, thereby optimizing collection routes and schedules. This not only reduces operational costs but also minimizes the carbon footprint associated with waste collection vehicles, aligning with broader environmental sustainability goals.

The selection of smart bins is also informed by their potential to improve the quality of life for Stirling's residents. By preventing overflow and reducing street litter, these bins would help maintain cleaner public spaces, contributing to a more pleasant urban environment. Moreover, the data collected from these bins can be used to inform and educate the community about waste management practices, creating a culture of recycling and environmental responsibility. This aspect is particularly crucial in smaller urban settings such as Stirling, where community engagement plays a vital role in the success of such initiatives.

Economic development is another critical factor driving the adoption of smart bins. By integrating innovative technologies into the city's waste management framework, Stirling positions itself as a forward-thinking community, attractive to investments and partnerships in the green technology sector. This can lead to job creation and stimulate local economies, showcasing the direct and indirect benefits of adopting smart city technologies.

Furthermore, the implementation of smart bins in Stirling serves as a scalable model for other small to medium-sized urban areas, demonstrating that smart city technologies are not exclusive to large metropolitan centres. It challenges the notion that smaller communities cannot benefit from or contribute to the subject of smart cities. By proving the feasibility and adaptability of such technologies in Stirling, the project sets a standard for similar urban settings, paving the way for broader adoption and customisation of smart technologies to meet the unique needs and challenges of diverse urban landscapes.

In summary, IoT-powered smart bins were chosen for Stirling to leverage technology in enhancing waste management efficiency, environmental sustainability, and community living standards, while also driving economic development and serving as a scalable model for other urban areas. This decision reflects a strategic approach to urban development, recognising the role of technology in addressing current challenges and opportunities in smaller urban settings.

2. Literature Review

2.1 Introduction

The emergence of the Internet of Things (IoT) marks the beginning of a transformative period in urban development (Kim et al., 2017), where smart technologies are increasingly being leveraged to address some of the most pressing challenges faced by cities today. This literature review is centred around the analysis of the diffusion of IoT-powered smart technologies. For this analysis, various frameworks and theories will be critically analysed in order to understand how existing literature can contribute to the research.

As outlined by Gracias et al (2023), smart cities embody the peak of technological integration, striving to enhance urban efficiency, sustainability, and quality of life through the deployment of smart technologies. In this context, smart bins represent a tangible application of IoT technologies aimed at improving waste management, this is to slowly integrate smart city-like technologies without a high level of disruption. These bins would utilise capacity sensors to monitor waste levels in real-time and solar panels for energy self-sufficiency, showcasing how IoT can contribute to more sustainable and efficient urban environments. As studied by Yang (2020) a very similar product exists in Songdo South Korea along with solar panels and capacity sensors these bins are also powered by IoT and are part of a much wider waste management system. The review will dissect the smart city concept to establish a foundational understanding of how technologies like smart bins fit within broader urban innovation strategies.

To navigate the complexities of technology diffusion in urban settings, it is imperative to explore theoretical frameworks that can effectively analyse the adoption and impact of smart technologies. This literature review will explore various technology diffusion models, examining how it applies to the possible adoption of smart bins within communities, identifying the key factors that influence the acceptance of such technologies. Additionally, the review will assess the applicability of other frameworks, such as the Technology Acceptance Model (TAM) by Fred Davies (1989), in predicting and understanding societal perceptions towards smart technologies as previously researched by Chuttur, M., (2009) .

The integration of smart technologies into urban landscapes is not without its challenges, as said by Sánchez-Corcuera (2019). Therefore, within this review there will also be an exploration of the potential barriers to adoption, ranging from technological to social and economic factors, and how these can be addressed within the frameworks being reviewed. By evaluating these frameworks, the intention is to identify best practices for facilitating the successful diffusion of smart technologies in cities, ensuring they meet the needs of the community and contribute positively to urban life (Long, 2016).

Furthermore, anticipating and understanding societal perceptions of IoT technologies is crucial for their successful implementation. This review will explore how frameworks such as TAM can be utilized to gauge public acceptance and readiness for smart technologies, thereby informing strategies for their effective introduction and integration into urban settings.

2.1 Background for the research

2.1.1 Smart City: A Concept

Nam and Pardo (2011) highlight the intricate nature of the "smart city" concept, noting its diverse interpretations and the lack of uniformity in its application across various cultural and geographical settings. Moreover, Albino et al. (2015) recognize that the term 'Smart City' encompasses a broad spectrum of elements, from cutting-edge information technology and entrepreneurial initiatives to frameworks of effective governance, citizen engagement, and sustainable practices. They also suggest that there's a common but sometimes misguided belief in the seamless integration of these components into everyday urban life, a notion that doesn't always align with the practical implementation and lived experience within smart cities. Bibri, S.E. (2018) calls for a revolutionary shift in how smart city models are conceived, underscoring the need to incorporate in principles of social equity, environmental protection, and inclusive governance to ensure that the evolution of smart cities is not only technologically progressive but also just and sustainable.

Exploring further, Javed et al. (2022) investigates the implications of 'smartness' within the smart city narrative, observing that in marketing, 'smartness' often implies an improvement in user experience—a key focus of this study aimed at amplifying community benefits. This emphasis on user experience is deliberate, seeking to appeal to a broader audience by choosing 'smart,' a term signifying approachability and simplicity, over 'intelligent,' which might come across as more elitist. Marsá-Maestre et al. (2008) expand on this idea by arguing that the true value of a smart city does not solely rest on technological innovation but also on its ability to meet the diverse needs of its citizens, thereby providing services that cater to a wide array of user preferences. This approach reinforces the importance of tailoring smart city projects to meet the genuine needs and desires of the community (Angelidou, M. 2015).

However, the deployment of smart city technologies is not without its hurdles. Kuziemski and Misuraca (2020) conduct extensive qualitative research, including numerous interviews, to reveal that publicly funded smart initiatives are at risk of being co-opted by private interests focused on profit, potentially side-lining or neglecting the welfare of the community. Moreover, the 'smart city' label can occasionally set unrealistic expectations for a flawless, technologically superior society, an ideal that contrasts with the more complex realities faced. Hollands (2008) points out significant concerns within smart city ventures, such as ensuring data privacy and security and addressing the potential for increasing social and economic disparities.

For smaller urban areas such as Stirling venturing into the realm of smart technology adoption, the aim should be to foster an ecosystem that is technologically forward-thinking yet deeply rooted in the actual experiences and needs of its citizens. Adopting this approach paves the way for a smart city that is truly sustainable, inclusive, and responsive to the community it serves.

2.1.2 Understanding the Internet of Things

The term "Internet of Things" (IoT), created by Kevin or in 1999, is used to describe a system that associates countless objects and devices such as sensors and actuators and other components that communicate and interact over the internet, facilitating data collection and observation. This technology marks the beginning of a significant shift in computing, driven by the widespread deployment of Wireless Sensor Networks (WSNs) in a multitude of applications. IoT's key features include extending the Internet to support diverse networks for seamless data exchange and broadening its reach beyond physical devices to encompass information and human activities. Applications range from enhancing urban infrastructure, such as smart parking and traffic systems, to reducing congestion and energy use. The essence of IoT lies in automating tasks through environmental sensing, data processing, and efficient execution. IoT has the potential to streamline and improve quality of life (Nižetić et al., 2020).

Madakam et al. (2015) meticulously traces the evolution of IoT, from its first stages in the 1980s with the first Internet-connected appliance—a Coke machine at Carnegie Mellon University—to the formalization of the concept by Kevin Ashton in 1999.
Mishra et al., (2021) provides a chronological account, highlighting the exponential growth of IoT devices and the significant milestones that have defined its trajectory towards becoming a global technology that infiltrates various aspects of modern life, which can be seen in Figure 1.

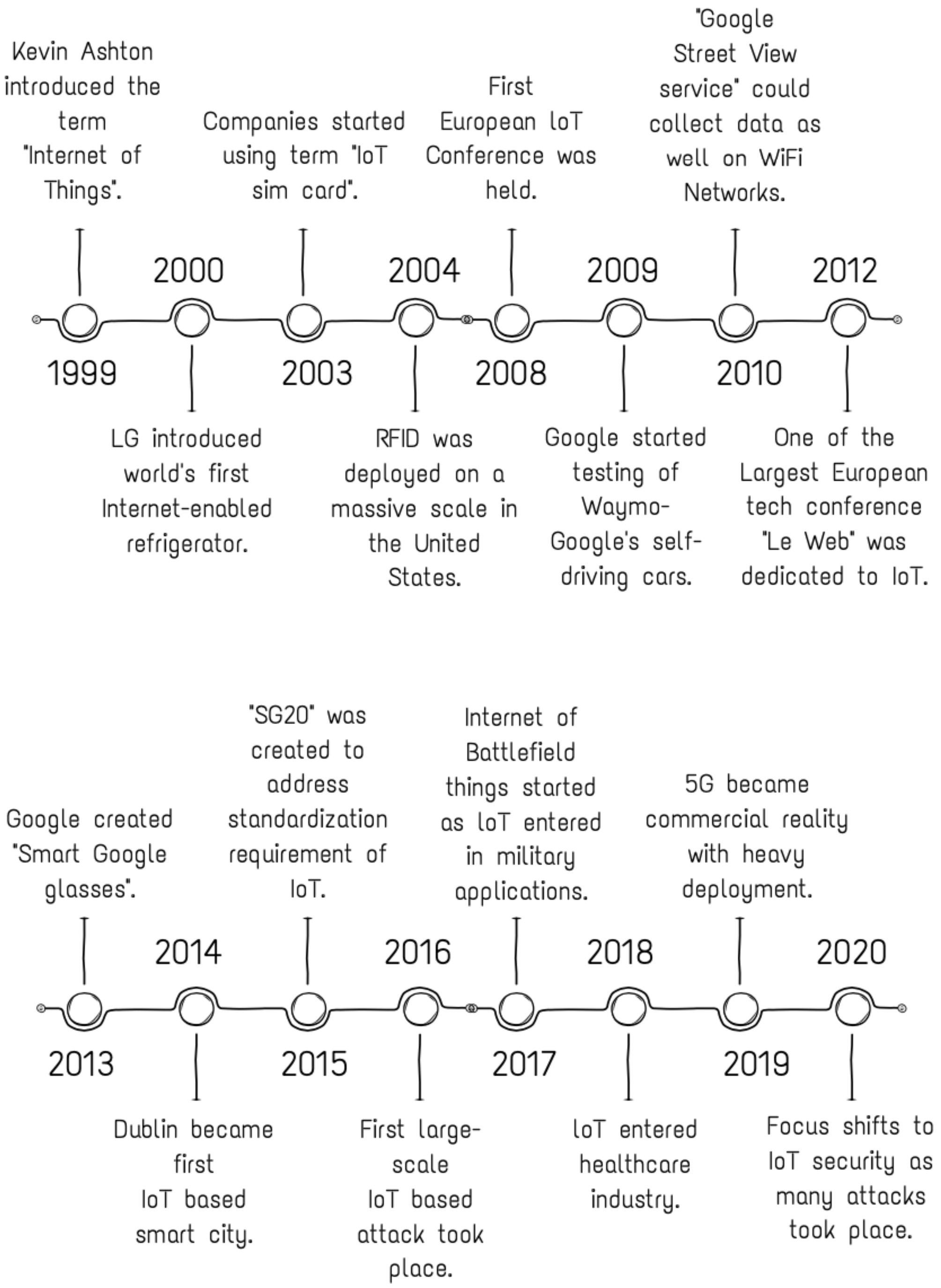


Figure 2.1: *Timeline Representation of IoT Evolution.* ***Source:*** *(Mishra et al., 2021)*

Madakam et al., investigates into the core technologies that form the backbone of IoT systems, including RFID, Internet Protocols, Electronic Product Codes, and a spectrum of wireless communication technologies like Wi-Fi and Bluetooth. It also highlights the critical role of actuators, sensors, Wireless Sensor Networks (WSN), and Artificial Intelligence (AI) in enabling IoT devices to interact dynamically with their environment. This comprehensive exploration not only elucidates the technological foundations and the evolutionary path of IoT but also acknowledges the challenges pertaining to standardization, and governance that loom large over its broader adoption. By providing a wide view on the historical context, technological groundworks, and future challenges, Madakam et al., establishes a robust foundation for future research and development within the Internet of Things (IoT) field.

As studied by Kramp et al., (2013) the Internet of Things (IoT) represents a transformative shift in the way digital and physical realms interact, marking an evolution towards a more connected, intelligent, and autonomous world. This shift, as explored in the book "Enabling Things to Talk: Designing IoT solutions with the IoT Architectural Reference Model," by Bassi et al., (2013) is underpinned by the convergence of various technological advancements, including identification technologies like RFID, networked sensors, and actuators, all contributing to the seamless integration of physical objects into the digital ecosystem

Following the studies by Kramp et al., (2013) the core challenge in realizing the IoT's full potential lies in the fragmentation and lack of interconnection among these technologies. Historically, solutions have been developed in isolation, tailored to specific application needs, for example the importance of creating a unified architecture and protocols for IoT-based smart cities. This has resulted in what can be referred to as "Intranet of Things" rather than a truly interconnected "Internet of Things." The lack of a universal protocol, akin to the Internet Protocol that governs computer communications, has impeded the evolution of the IoT (Malhotra, 2021).

The study by Zanella et al. (2014) on the Padova Smart City project presents a comprehensive application of IoT technologies for environmental monitoring within an urban context. Utilizing wireless sensor networks and IPv6/6LoWPAN for data communication (Kim et al., 2022), the project highlights the pivotal role of gateway devices in bridging sensor data with the wider Internet infrastructure. Zanella et al. detail their data collection approach, deploying sensors to monitor parameters such as temperature, humidity, light, and benzene levels, thereby offering a view of the urban environmental landscape over a week. The analysis reveals clear daytime patterns and the impact of urban dynamics on air quality, with intriguing observations on benzene levels during different traffic conditions. This contribution by Zanella et al. enriches the literature on smart cities by demonstrating the practicality and value of IoT in urban environmental management, emphasizing the need for nuanced data analysis to inform city planning and policy. IPv6/6LoWPAN is explained in Figure 2, adapted from the study by Roth et al., (2012). These are critical aspects to consider when debating the implementation of such technologies in Stirling.

Aspect	IPv6	6LoWPAN
Definition	The most recent version of the Internet Protocol, designed to address the limitations of IPv4.	A communication protocol that enables IPv6 communication over Low-Power Wireless Personal Area Networks.
Primary Motivation	To provide a vastly larger address space and introduce improvements over IPv4.	To enable small, low-power devices to communicate with internet-connected applications using IPv6.
Use Case	General internet networking, especially where a large number of unique IP addresses are required.	Internet of Things (IoT) applications where devices are low-power and bandwidth is limited.
Compatibility	Directly compatible with modern internet infrastructure.	Enables IoT devices to connect over the internet using IPv6, facilitating interoperability.
Networking	Supports a wide range of networking types and sizes, from small home networks to large enterprise and global internet service providers.	Primarily used in personal area networks (PANs), particularly for connecting low-power IoT devices in a mesh network configuration.
Importance for IoT	IPv6 enables every device in the IoT ecosystem to have a unique IP address, facilitating direct, end-to-end connectivity across the internet. This allows potentially billions of devices to be interconnected globally.	6LoWPAN makes it feasible for resource-constrained devices to join the IoT world This protocol bridges the gap between limited capability devices and the broader IPv6 internet, making it a cornerstone for the practical deployment of IoT solutions.

Figure 2.2: *IPv6 and 6LoWPAN Explanation* ***Source:*** *(Author, 2024)*

2.2 Theories of adoption

2.2.1 Diffusion Theory

The application of Rogers' (1962) Diffusion of Innovations model is critical in understanding and facilitating the adoption of new technologies in these settings. This model outlines a specific process for the adoption of an innovation, encompassing stages like knowledge, persuasion, decision, implementation, and confirmation. Using frameworks can facilitate the identification of the critical factors city planners and policymakers need to consider when developing strategies that address the concerns of various population segments, including early adopters, the early majority, late majority, and laggards. The framework is outlined and explained below [Figure 3 and Figure 4].

Developing from this, Elfreda Chatman's influential work, presented in the "Journal of the American Society for Information Science" (1986), explores the intricacies of diffusion theory with a comprehensive review and critical analysis aimed at unpacking its conceptual framework and empirical validity. Chatman's effort to clarify the theory's scope is crucial, as she defines diffusion theory as a model concerned with the mechanisms through which innovations are communicated and adopted within a social system over time. This exploration is not only academic; it serves as a bridge connecting various disciplines, including sociology, communication, and economics, to forge a distinct understanding of how innovations infiltrate society.

Additionally, Chatman's analysis exposes the theory's limitations, particularly its overemphasis on individual decision-making processes at the expense of acknowledging the broader societal, cultural, and institutional forces at play. Through the examination of empirical tests and case studies, the author highlights the theory's partial success in capturing the complex dynamics of innovation adoption while also identifying significant gaps in the theory's ability to account for the multifaceted influences on diffusion processes.

Furthermore, Chatman's work is instrumental in applying diffusion theory within the realm of information science, offering insights into the adoption of information technologies. By analysing the barriers to technology adoption and the role of social networks in information dissemination, the author lays the groundwork for future research that seeks to refine diffusion theory. Chatman advocates for an interdisciplinary approach that leverages insights from across fields to enhance the theory's applicability and address its shortcomings. Her critical review not only underscores the potential of diffusion theory in understanding innovation spread but also charts a path forward for deepening its theoretical and practical contributions to information science and beyond.

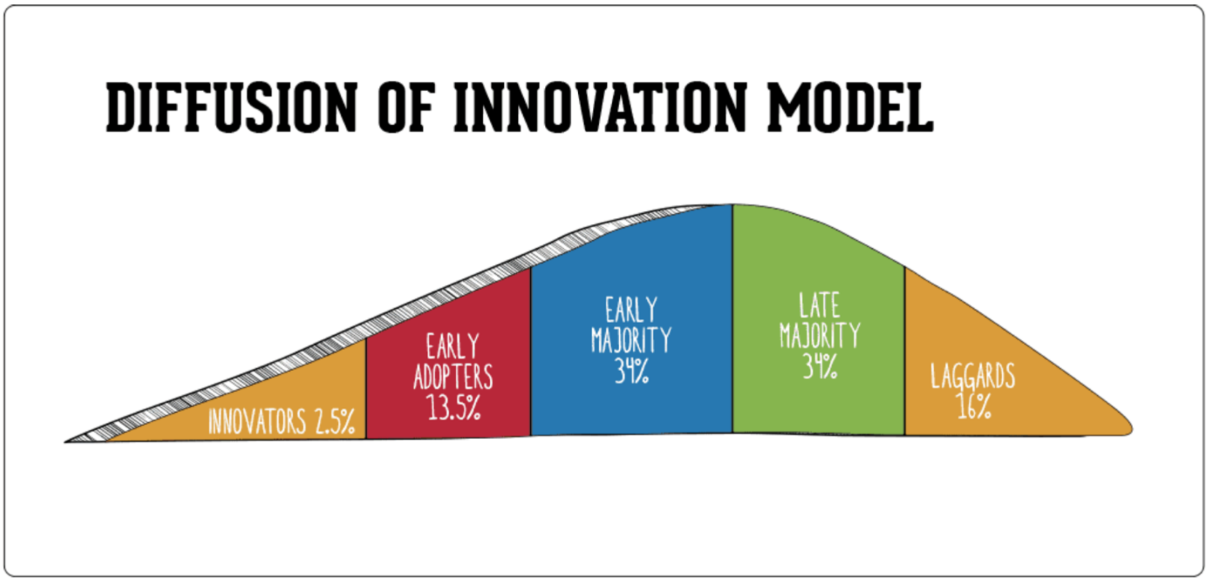


Figure 2.3: *Diffusion of Innovation Model.* ***Source:*** *(Hanlon, A 2013)*

Eaton and Kortum (2001) share the core idea of diffusion theory although they approach the matter from a different perspective. In the study "International Technology Diffusion: Theory and Measurement" the authors research diffusion theory within the sector of international technology diffusion, this offers a perspective that bridges the gap between the global dissemination of technological innovations and the localized benefits acquired from such dissemination. At the heart of their analysis lies a model that not only captures the inception and global spread of new technologies but also maps out the interplay between a country's pace of technological adoption and its resultant productivity ranking on the global stage.

The authors develop a quantitative model to measure how technologies spread globally, emphasizing the role of geographical proximity, cultural similarities, and trade connections in facilitating this process. Their analysis, utilizing patent data and international trade information, confirms that countries with greater access to global innovations tend to experience enhanced economic performance due to improved productivity from advanced technologies.

This gradual diffusion underscores a key insight: while the countries at the forefront of innovation enjoy the highest levels of productivity, their technological contributions also disseminate growth and development beyond their borders. By articulating this balanced view, Eaton and Kortum's work sheds light on the complex mechanisms supporting international technology diffusion, emphasizing the role of both domestic innovation and global collaboration in fostering economic growth and productivity enhancements across nations. Their findings advocate for an understanding of diffusion theory, suggesting that the benefits of technological advancements are not confined to their origins but are spread worldwide, thereby influencing a wide array of socio-economic outcomes.

Diffusion theory is critical to this ongoing research as it offers direct insights into the challenges and stages that come with technological adoption.

Category	**Explanation**
Innovators	First category to try new technologies, often driven by a desire to experiment.
Early Adopters	Individuals who adopt new technologies quickly, often setting trends for others.
Early Majority	Individuals who adopt new technologies after seeing its benefits from early adopters.
Late Majority	Individuals who adopt technology after the late majority, influenced by peer pressure.
Laggards	The last category to adopt, preferring traditional methods, often only adapting out of necessity.

Figure 2.4: *Diffusion of Innovation Categories* ***Source:*** *(Author, 2024)*

2.2.2 Technology Acceptance Model

N. Marangunic and A. Granic (2015) explore the depths and dimensions of the Technology Acceptance Model (TAM), a fundamental framework initially introduced by Fred Davis to assess technology acceptance behaviours [See Figure 5]. Using a concept-centric approach, the authors explore the theoretical foundations of TAM, tracing its lineage from the Theory of Reasonable Action (TRA) and the Theory of Planned Behaviour (TPB), and scrutinize its evolution, highlighting the critical roles of perceived ease of use and perceived usefulness as mediators in technology adoption.

Marangunic and Granic's of TAM's extensions, modifications, and varied applications across different domains, offering a detailed understanding of its adaptability and enduring relevance in technology acceptance studies. Their review not only reaffirms TAM's significance in the contemporary digital landscape but also paves the way for future research, suggesting new avenues for exploring technology acceptance patterns. By cataloguing the model's trajectory and proposing potential areas for further analysis, Marangunic and Granic significantly contribute to the field, underscoring the model's versatility and its capacity to provide insightful perspectives on user interactions with technology.

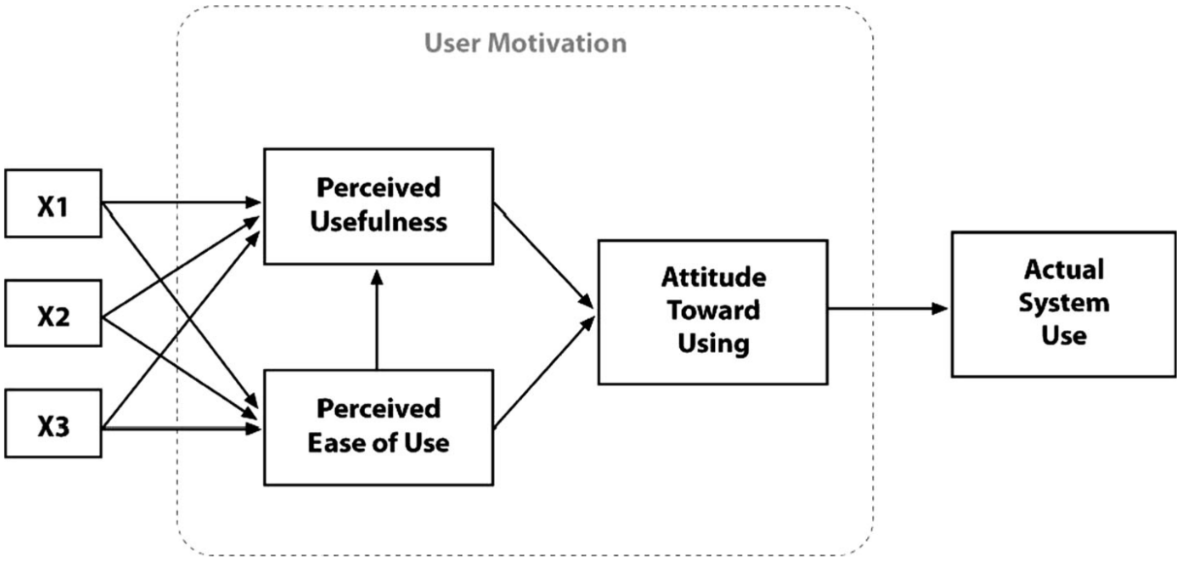


Figure 2.5: *Technology Acceptance Model.* ***Source:*** *(Davies, 1986)*

Boughzala, I., (2014) clearly depicts the differences between TAM, TAM2 and TAM3 in Figure 6. This is crucial when attempting to choose an appropriate model for the scope at hand. Furthermore, Zhang (2010) sheds light on TAM2, through their research on Adoption of Mobile Information Technology by Homecare Nurses, they clarify how TAM2 was designed with organizational technology acceptance in mind, emphasizing factors such as output quality and job relevance. Such aspects are less relevant within the research at hand.

Additionally, Setiyani (2021) explores TAM3 within their research, uncovering how the model considers not just perceived ease of use and usefulness, but also factors such as subjective norms, image, self-efficacy, anxiety, facilitating conditions, and perceived enjoyment.

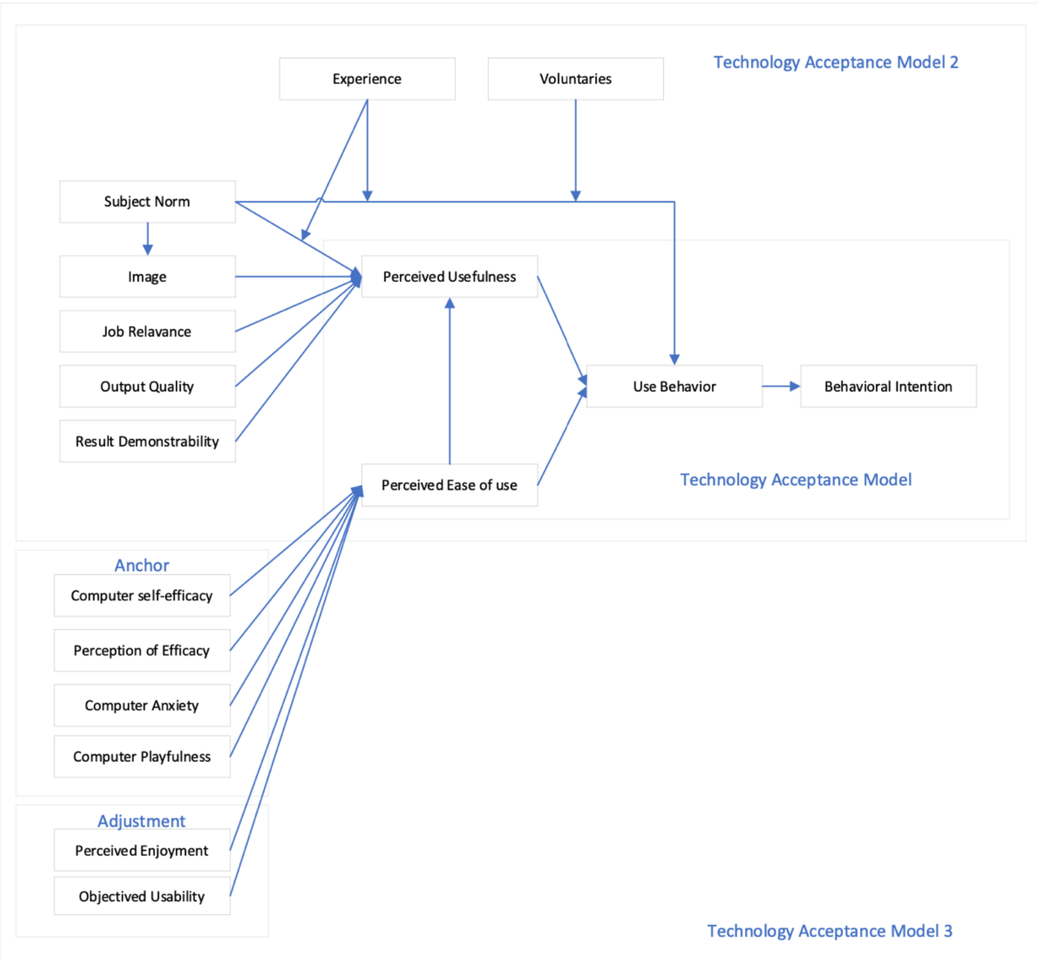


Figure 2.6: *TAM, TAM2, TAM3.* ***Source:*** *(Adetimirin, A., 2015)*

The study by Sepasgozar et al., (2019) resents a detailed investigation into the adoption and acceptance of Urban Services Technology (UST) in the context of developing smart cities, with a focus on the Technology Acceptance Model (TAM) as a foundational theoretical framework. The research, led by Samad Sepasgozar and his team, explores the multifaceted aspects of technology acceptance, specifically within the urban services sector, aiming to enhance our understanding of how new technologies are received and integrated into urban settings.

The study assesses various factors influencing technology acceptance drawing from a survey conducted across major Iranian cities. This approach allows for an examination of user perceptions towards Urban Services Technologies, encompassing elements such as perceived security, ease of use, usefulness, and compatibility, among others. The Technology Acceptance Model (TAM), renowned for its reliability in predicting user acceptance of new technologies, is accurately applied to the urban context, incorporating additional constructs from social cognitive theory to enrich the analysis.

Results from the research reveal a complex interplay of factors contributing to technology acceptance, highlighting the paramount importance of constructs such as self-efficacy, work facilitation, and compatibility in shaping users' intentions to adopt UST. Interestingly, the study challenges conventional assumptions regarding cost as a primary barrier to technology adoption, instead uncovering a more intricate set of priorities and concerns among urban citizens.

By integrating insights from TAM and social cognitive theory, the research culminates in the development of the Urban Services Technology Acceptance Model (USTAM), offering a comprehensive framework to guide future smart city initiatives. This model advances theoretical understanding and provides practical implications for policymakers, urban planners, and technology developers seeking to foster technology acceptance in urban environments.

2.3 Understanding Community Perception

2.3.1 Effects of Smart City Technology on community

Smart city technology holds the potential to revolutionize community dynamics across social, political, and environmental domains. From an environmental standpoint, smart technologies can significantly contribute to the development of sustainable urban ecosystems. Hossein Motlagh et al. (2020) illustrate this with examples such as Internet of Things (IoT)-enabled systems, which can manage resources more efficiently, optimize energy use, and reduce waste through smart recycling systems, thereby fostering a cleaner, greener urban environment and reducing carbon footprint.

Considering the economic perspective, Rossi (2015) found that the implementation of smart city initiatives can act as a stimulus for growth, attracting businesses eager to leverage the advantages of a sophisticated, interconnected technology infrastructure, which can invigorate local economies and lead to job creation. This highlights the need for careful planning and consideration to ensure equitable access and benefits from smart city initiatives, preventing the exacerbation of existing societal divides. This is crucial as such initiatives risk favouring those who are already financially stable or technologically savvy.

Kontokosta and Hong (2020) highlight substantial concerns about security and privacy in the context of smart technologies. Their research involved the collection and analysis of personal data, focusing on measuring and understanding complaint behaviour in relation to the actual problems faced by communities. Their findings suggest it is essential to implement strict security measures to protect personal privacy and prevent the misuse of data.

When trying to understand the effects that smart city technology can have on a community it is worth analysing the various scenarios in which this technology can be presented. Anagnostopoulos et al. (2015) delve into the realm of waste management within smart cities, emphasizing the critical role of Internet of Things (IoT) technologies in refining the efficiency of high-priority waste collection. Their study is based on the development and evaluation of four innovative dynamic waste collection models: the Dedicated Trucks Model (DTM), Detour Model (DM), Minimum Distance Model (MDM), and Reassignment Model (RM). These models are designed to adjust waste collection routes in real-time, leveraging data from sensors equipped on waste bins. The authors' methods employ simulations based on real-world data from a smart city's waste management system, distinguishing between regular and high-priority waste bins. Their findings reveal that each proposed model possesses unique advantages tailored to different operational scenarios within smart cities. This is a good example to consider when deciding the best way to diffuse a technology within society.

Overall, the impact of smart city technologies on communities is multifaceted. While they offer prospects for improved governance, economic growth, and environmental sustainability, they also bring forward challenges related to social justice, privacy, and security. Zavratnik et al. (2020) suggest that a community-centred approach is advantageous in the evolution of smart cities. The author suggests it would ensure that the development of smart cities encompasses more than just technological advancement, focusing instead on the broader well-being and inclusivity of the community. Adopting this perspective is essential for cities like Stirling to fully harness the benefits of smart technologies.

2.3.2 Anticipating Society Perception

When considering integrating smart technologies into smaller urban areas like Stirling, it is beneficial to consider their adoption in other cities. The response to past smart city technologies implementation has been a blend of optimism and concern. As suggested by Harrison and Ian Harrison (2011), in the UK, smart cities are acknowledged for their tangible benefits, including improved public services, enhanced security, reduced pollution, and better traffic management. Moreover, Brown et al., (2020) analysed 26 UK cities and found that many of these have significantly invested in smart city initiatives, therefore the Stirling Council could be open to this idea as well, aiming to enhance urban living through augmented connectivity and data-driven solutions.

Furthermore, Bokolo, A.J., (2023) explores the diffusion theory further. He carried out mixed methods research to articulate the process of innovation adoption in smart cities, identifying five distinct stages in the adoption lifecycle. The first stage, "Knowledge," is where individuals become aware of the innovation but do not possess exhaustive information. This is followed by "Persuasion," a phase in which individuals develop either favourable or unfavourable attitudes towards it. Next is the "Decision" stage, where individuals actively engage in activities that lead them to either adopt or reject the innovation. The fourth stage, "Implementation," sees the innovation put into practical use. Finally, the "Confirmation" stage, where individuals seek additional validation for their decisions. This structured framework provides a deeper understanding of how smart city technologies are gradually embraced by different segments of the population.

Upon demographic analysis and a survey with 545 participants, Georgiadis et al. (2021) found that despite the potential benefits, public reluctance persists, primarily due to data privacy and security concerns. The authors discovered that while the general attitude towards this topic is positive, the adoption process is hindered by factors such as a lack of technical skills among the public, financial limitations, legal barriers, and a general mistrust in digital initiatives. Ethical concerns, including increased surveillance and cybersecurity risks, also contribute to public apprehension.

Similarly, Wani and Ali (2015) found that understanding these apprehensions through the lens of diffusion theory can assist in devising more effective, community-focused strategies for implementing smart city technologies, leading to a smoother transition and broader public acceptance. These insights indicate that community enthusiasm for the efficiency and modernization promised by smart city technologies is high, provided certain practices are adhered to.

This literature review addresses the complexities of smart cities, their community impact, and public perception, emphasizing the need for inclusive and ethical approaches. It highlights both the transformative potential and the challenges of smart city technologies, stressing the importance of addressing privacy, equity, and security concerns. This analysis forms the foundations of this research, guiding the future exploration of effective smart city technologies implementation in small urban settings like Stirling.

2.4 Conclusion

As previously mentioned, the integration of Internet of Things (IoT) technologies is a crucial step towards realizing the vision of sustainable and efficient smart cities, especially in the context of urban development. The smart bin systems in Stirling, with their capacity sensors and solar panels, showcase the potential of IoT to revolutionize urban management by improving efficiency, reducing waste, and promoting environmental sustainability. The exploration of theoretical frameworks like diffusion theory and the Technology Acceptance Model (TAM) offers insights into technology adoption dynamics, highlighting the importance of societal perceptions and user experiences in deploying smart technologies effectively.

This literature review has analysed the adoption and integration of smart technologies in urban settings, focusing on IoT and its role in waste management. By examining frameworks like diffusion theory and TAM, it emphasizes understanding the factors influencing smart technology acceptance within communities. This review confirms that integrating IoT smart technologies can significantly enhance smart city development, making them technologically advanced, sustainable, resilient, and inclusive. The adoption of smart bins in Stirling is driven by community openness and recognized benefits, unaffected by age differences. Key drivers include positive perceptions of effectiveness and usability. Barriers are minimal but include the need for educational outreach to address knowledge gaps and ensure inclusive access, addressing concerns of a small but significant minority. Leveraging IoT for urban management can develop substantial benefits, setting the stage for future innovations in smart city strategies. Lastly, this research provides a framework and analysis of best practices for those aiming to utilize IoT's transformative power in developing the smart cities of tomorrow.

3. Methodology

3.1 Research Design

This study is driven by the obligation to fulfil the following objectives: 1) Define the concept of a smart city and explore why it is often linked with major metropolitan areas. 2) Assess the feasibility of deploying AI-enabled smart waste bins in Stirling, considering the town's distinctive characteristics, population, and infrastructure. 3) Investigate the possible societal impacts, both positive and negative, of introducing intelligent waste management solutions, emphasizing their effect on living standards. 4) Gather and examine feedback from diverse groups, including residents, businesses, and community groups, to capture their opinions, requirements, and apprehensions about the potential deployment of smart bins and recycling stations. 5) Gather the research findings into practical advice for the municipal authorities and other relevant parties, providing guidelines on best practices and identifying possible challenges.

The methodology to answer these research objectives utilises quantitative analyses to fully explore the possible adoption and effects of smart city innovations, maintaining a specific focus on advanced waste management technologies such as IoT-Powered smart bins. This study is recognized as abductive, merging first-hand information with established theories such as the theory of diffusion by Evrett Rogers and the technology acceptance model by Fred Davis, also known as TAM .

Moreover, the research adopts an exploratory approach to investigate how Stirling is associated to potential city-wide technological advancements, such as the adoption of IoT powered smart bins. Primary data will be collected through structured interviews and entries from a detailed survey. Surveys, aimed at quantifying data, will involve a randomly chosen portion of the population, including anyone over the age of eighteen who resides in Stirling. This method will ensure a broad spectrum of community views on smart city projects, covering various aspects such as tech-savviness, origins, and other demographic details, while offering the publics views on the matter. The survey will be piloted and tested by a trusted member of the Stirling community before approaching the survey respondents.

The quantitative data analysis will be meticulously conducted using SPSS software, a robust statistical analysis tool. This approach will facilitate a comprehensive exploration of patterns, trends, and relationships concerning the acceptance and impact of smart city technologies in Stirling. By leveraging SPSS's advanced analytical capabilities, the aim will be to uncover insightful correlations, variances, and potential predictive factors that can inform the effective implementation and public reception of these technologies.

This research's strategy, based on qualitative data, is aimed at extrapolating intel in order to deliver actionable recommendations to the local authorities and interested parties, developing well-informed plans for possible forthcoming smart city projects as well as satisfying Research Objective 3 (RO3). By pinpointing major tendencies, obstacles, and opportunities, the study will make a meaningful contribution to the comprehension of Stirling's smart city environment.

3.1.1 Justification of Methodology

The employment of a quantitative methodology in this investigation is fundamental due to the intricate topic of smart city solutions, particularly their implementation and impact within the Stirling context. This approach, focusing exclusively on quantitative research techniques, is critical for forming a robust evidence base. The quantitative strategy, utilizing metric surveys, is dedicated to gathering objective data, setting the foundation to uncover trends, patterns, and relationships in the adoption and effectiveness of smart city initiatives. This component is essential for grounding the study in concrete, quantifiable facts, offering a detailed snapshot of the present and future trajectories of smart city projects.

By prioritising a quantitative method, the research aspires to define the effect of smart city technologies, providing a focused perspective on statistical and numerical examination. This choice was made to ensure a comprehensive evaluation based on empirical data, sidestepping the subjective evidence typically captured through qualitative methods. Consequently, this study aims to deliver a clear, data-driven picture of the smart city landscape in Stirling, enhancing the ability to formulate precise, actionable insights for the local government and stakeholders engaged in shaping future smart city strategies. A stakeholder analysis is available and can be found under Figure 3.2.

The strategic decision to adopt a quantitative-only approach is vital for acquiring an in-depth understanding of the potential and challenges of Stirling’s smart city framework from a numerical perspective. It ensures that the conclusions are based on empirical evidence, facilitating targeted, evidence-based recommendations for enhancing the city's smart technology initiatives. This quantitative focus emphasizes the importance of measurable outcomes and data-driven decision-making in advancing the smart city agenda, aiming to achieve tangible improvements and sustainable growth in Stirling's urban development.

3.1.2 Sampling

In this research, surveys aimed to target between 120 and 150 Stirling residents, utilizing a non-probability and voluntary snowball sampling technique to assemble a broad and diverse group. This method is designed to include individuals from a variety of age groups, technological proficiency levels, and socio-economic backgrounds, ensuring a broad spectrum of viewpoints is represented. The selection process deliberately prioritizes reaching out to participants through existing networks and encourages them to recommend further participants, therefore expanding the pool of potential respondents. This technique is particularly beneficial in capturing insights from hard-to-reach segments of the population, who might not typically engage in traditional survey methods but are equally important for understanding the community's stance on smart city initiatives.

By fostering an environment where participants are sourced through personal connections, the research aims to tap into a deeper layer of community insights, capturing not only surface-level opinions but also the underlying reasons and motivations behind those views. This approach is helpful in constructing an idea of the local sentiment towards smart city projects, incorporating both enthusiastic views and more critical opinions. Moreover, the inclusion of a wide array of demographic characteristics among participants helps to identify any patterns or trends in perceptions that may relate with specific groups, adding another layer of depth to the analysis.

Such a strategy guarantees that the collected data is inclusive and varied, offering a general view of local thoughts regarding smart city projects. The rationale behind engaging such a wide segment of the community is to secure insights that accurately reflect the collective perspective, thereby increasing the reliability of the research outcomes. Additionally, this methodology serves to highlight any disparities in access or attitudes towards technology-based urban development, guiding policymakers towards more impartial and inclusive strategies. Ultimately, the research aims to not only grasp current sentiment but also to uncover potential drivers and barriers to the adoption of smart city technologies, facilitating a more targeted and effective approach to urban planning and development.

3.2 Quantitative Research Design

3.2.1 Justification of Questions

The survey from the quantitative component is designed to gather comprehensive demographic information and grasp public opinion regarding waste management practices in Stirling, with a particular focus on the potential introduction of AI-powered smart bins. By collecting demographic data, such as age, occupation, and area of residence, the aim is to understand the diverse perspectives across different segments of the Stirling community. The questions related to the current waste management system's effectiveness and the city's recycling efforts are intended to establish a baseline of public satisfaction and identify areas for improvement. The introduction of AI-powered smart bins represents a unique approach to enhance waste sorting and recycling efficiency. Therefore, we are seeking feedback on the community's awareness of such technologies, their potential benefits, concerns, and the willingness of residents to utilise these bins. This information will be invaluable in assessing the feasibility, expected impact, and any challenges that might arise with the implementation of this technology. The survey's findings will contribute to making informed decisions aimed at improving Stirling's waste management system and advancing environmental sustainability.

The Technology Acceptance Model (TAM) framework, which predicts how users come to accept and use a technology, is well-reflected in the questions designed to assess the potential adoption of IoT Smart Bins in Stirling. Question 7, which inquiries about the perceived improvement of waste management through smart bins, aligns with **Perceived Usefulness**, a core TAM concept indicating the degree to which a person believes that using a particular system would enhance their job performance or in this context, the community's waste management efficiency. Question 11 targets **Perceived Ease of Use** by asking about the user-friendliness of smart bins for all residents, another fundamental aspect of TAM, as technologies perceived as easy to use are more readily accepted and integrated into daily routines. Question 12 explores the **effectiveness of the technology** within smart bins, further exploring into perceived usefulness by evaluating the specific functionalities (e.g., sensors, IoT connectivity) that could lead to more efficient waste management. Finally, Question 13 measures

Behavioural Intention, asking about the willingness to use smart bins regularly, assuming they are as useful as expected, which directly correlates with the likelihood of the technology's adoption and consistent use. Together, these questions capture the TAM's focus on understanding user acceptance through perceived ease of use, usefulness, and the resulting behavioural intentions towards technology, providing insights into the community's readiness to adopt smart bin technology.

The selected questions for the questionnaire are detailed designed around the Diffusion of Innovations theory, aiming to measure the potential adoption of IoT-powered smart bins in Stirling by addressing key aspects such as compatibility, trialability, relative advantage, perceived barriers, and overall community support.

Question 8 explores compatibility, evaluating how well smart bins align with Stirling's communal values and practices, crucial for ensuring the technology's resemblance with local lifestyles.

Question 9 assesses residents' willingness to engage with this innovation, reflecting trialability and the community's openness to experiment with new technologies. The relative advantage of smart bins, particularly their impact on public cleanliness, is examined in Question 10, determining if the technology offers significant improvements over existing waste management systems.

Questions 14 and 15 identify potential concerns and challenges, addressing the complexity and perceived barriers that could obstruct adoption. Lastly, Question 17 measures the overall support for smart bins, a critical indicator of the community's readiness to embrace this innovative solution. Together, these questions meticulously capture the multifaceted decision-making process influenced by the theory's principles, essential for understanding the community's acceptance and support for smart bins. A detailed table representing this is shown in Figure 3.1

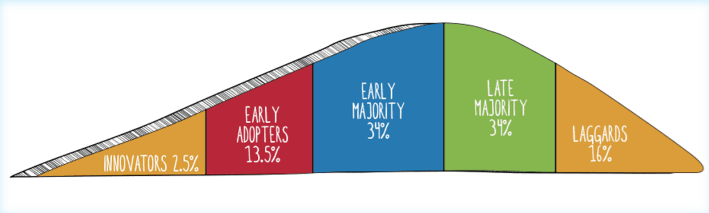
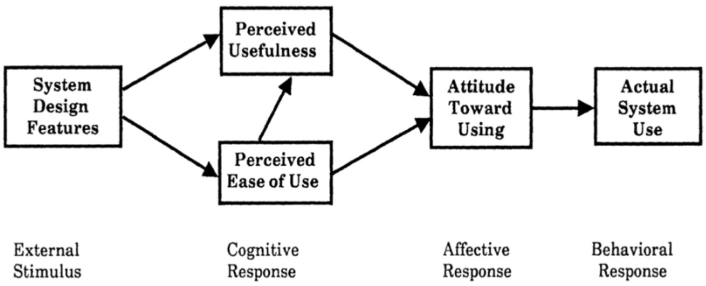
Framework Utilised	Survey Question
	8. How compatible do you believe smart bins are with the values, needs, and practices of the Stirling community? 9. How willing would you be to use IoT-Powered Smart Bins if they were available in Stirling? 10. Do you think the implementation of Smart bins would improve the cleanliness in public areas? 14. Do you have any concerns about the use of IoT-powered smart bins in Stirling? 15. Do you think the implementation of smart bins could present challenges for the Stirling community? 17. Would you support the implementation of smart bins in Stirling?
	7. Do you believe IoT Smart Bins could improve waste management in Stirling? 11. Do you think smart bins would be easy to use for all residents? 12. How effective do you think the technology within smart bins (e.g., sensors, IoT connectivity) would be in managing waste? 13. Assuming smart bins are as useful as expected, how willing would you be to use them regularly?

Figure 3.1: *Framework and Survey Questions Correlation* ***Source:*** *(Author, 2024)*

3.2.2 Data Analysis

Data collected from the survey will undergo a thorough analytical study, utilising SPSS (Statistical Package for the Social Sciences) software, a robust platform designed for the execution of a wide range of statistical tests. The initial stage of the analysis will involve descriptive statistical analyses, which serve to summarize the dataset and provide a clear overview of the respondents' characteristics and responses. This foundational step is essential for establishing a baseline understanding of the data, enabling the identification of general trends and distributions within the collected information.

Following the descriptive analysis, the study will employ cross-tabulation analysis to examine the relationships between different variables. This technique is particularly useful for identifying patterns and associations that may exist between respondents' demographics and their attitudes or experiences with technology within the smart city context. Furthermore, correlation testing will be conducted to assess the strength and direction of relationships between variables, offering preliminary insights into potential factors that influence technology uptake and its perceived effectiveness.

The study will include a regression analysis, which, in this context, will be important in unravelling the complex dynamics that underpin technology adoption and its effectiveness, providing an understanding of the variables that significantly impact these outcomes. Through these comprehensive analytical processes, the research aims to uncover patterns and insights, crucial for enabling informed decision-making by local authorities and stakeholders. An analysis of the stakeholders is available in Figure 8. By leveraging the capabilities of SPSS software for these analyses, the study aspires to contribute valuable evidence-based recommendations that can guide strategic planning and implementation of smart city initiatives, ensuring they are effectively tailored to meet the needs and expectations of the community.

Stakeholder Group	Interest	Impact	What Stakeholders Value
Municipal Authorities	Decision-making for implementation	High; can approve or reject project proposals	Guidelines for implementation, identifying potential challenges
Local Residents	Directly impacted by changes in living standards	High; quality of life and environmental impact	Societal impacts, operational efficiency, convenience
Community Groups	Advocacy for societal benefits or concerns	High; influence public opinion and policy	Community engagement, sustainability, inclusivity
Environmental NGOs	Sustainable practices and environmental impact	High; advocacy for environmental protection	Positive environmental outcomes, sustainable development
Urban Planners	Integration of smart solutions within the city	High; planning and design influence	Infrastructure compatibility, smart city concepts
Waste Management Companies	Operational aspects of waste collection and recycling	High; operational efficiency and cost-effectiveness	Feasibility of implementing smart bins, operational impacts

Figure 3.2: *Stakeholder Analysis* ***Source:*** *(Author, 2024)*

3.4 Ethical Consideration

Ethical considerations are critical within this research process. Participants will contribute voluntarily; confidentiality and anonymity has been adhered to for all involved. The implemented secure data storage and access control, ensure top-level information security. The study will follow ethical guidelines, emphasizing respect for individual privacy, harm prevention, and the right for participants to withdraw at any point without repercussions.

The consent process will be outlined, ensuring participants are fully aware of the study's purpose and the nature of their involvement. This process guarantees that consent is not only informed but also voluntary.

Additionally, special attention has been paid to the ethical implications of data interpretation and publication, ensuring that findings are presented in a way that respects the dignity and diversity of the community under study. Misrepresentation or misuse of data is rigorously avoided to preserve the authenticity and ethical integrity of the research outcomes.

To address unforeseen ethical issues, an ethical review will be submitted and approved to allow for adjustment of the study's protocol as necessary. This proactive approach ensures that the research maintains the highest ethical standards throughout its duration. These measures underscore the dedication to upholding ethical conduct in line with academic requirements, while also enhancing the research's integrity and its contribution to the field.

3.5 Limitations

Despite its comprehensive design, the study acknowledges several limitations that merit careful consideration. The reliance on self-reported data through qualitative interviews introduces a layer of subjective bias. Participants’ perceptions and narratives about technology adoption might be influenced by personal experiences or beliefs, potentially distorting the findings. To mitigate this, employing a mixed-methods approach could cross-validate data, enhancing legitimacy by corroborating findings across qualitative and quantitative measures. Furthermore, the author recognises that the sample size of 129 survey respondents may be insufficient to generate statistically valid conclusions.

Quantitative data, while providing a broad overview, may not fully summarise the complex nature of smart city technology evolution. The rapid pace at which technology advances means that findings might quickly become outdated, challenging the study’s long-term relevance.

Furthermore, the research’s focus on Stirling, with its unique societal context, limits the generalizability of the findings. Urban areas with differing characteristics might experience technology adoption in distinct ways.

4. Research Findings

This chapter presents the research findings related to the study outlined in Chapter 1, aiming to find answers to the research objectives. The intention is to explore both the technological feasibility and the community's openness to integrating such innovations into their daily lives.

4.1 Introduction

This study presents an examination of the opinions of Stirling residents on the possible integration of Internet of Things (IoT) technology within urban waste management systems, specifically analysing the potential deployment of IoT-powered smart bins in Stirling. It assesses the readiness and attitudes of the local population towards adopting this technology, with a focus on identifying demographic variations in knowledge and acceptance. The investigation includes an evaluation of the correlation between age and various factors such as willingness to use the technology, perceived improvements in waste management efficiency, and potential challenges and concerns that could arise from the implementation of such a system. The methodology comprises quantitative analyses, utilizing regression, correlation, and cross-tabulation to explain the collected data. The findings are intended to support policymakers and urban planners in making data-driven decisions that align with the technological trends and public sentiment.

4.2 Key Research Findings

The data analysis presented utilizes SPSS to extract meaningful insights regarding the adoption of IoT-powered Smart Bins in Stirling. The section starts with a description of the statistics which lays the groundwork, followed by normality tests to identify the suitable analytical techniques. The selected methods include regression, correlation, and cross-tabulation analysis, all chosen for their relevance to our research objectives. These methods were chosen in order to fulfil research objectives 2,3 and 4.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age	129	1.00	2.00	1.0853	.28037
Waste_Management_Satisfaction	129	11	13	11.89	.731
Effective	129	11	13	11.81	.686
Iot_Knowledge	129	1	2	1.38	.487
Improvement_3to5	129	3	5	4.00	.729
Compatibility_3to5	129	3	5	3.97	.695
Willingness_3to5	129	3	5	4.19	.726
Improve_Cleanliness_3to5	129	3	5	4.15	.663
Ease_of_Use_3to5	129	3	5	3.97	.728
Technology_Effectiveness_3to5	129	3	5	3.97	.739
Wilingness_to_use_3to5	129	3	5	4.41	.657
Concerns	129	1	2	1.23	.424
Challenges	129	1	2	1.22	.419
Occupation	129	6.00	79.00	9.5426	6.66967
Valid N (listwise)	129				

Figure 4.1: *Descriptive Statistics*

The descriptive statistics above directly relate to the research objectives of this study. Understanding if the age of participants influences the practicality of IoT-powered Smart Bins in Stirling is important and directly relates to RO2, as well as and providing essential data for understanding stakeholder perspectives RO4.

High satisfaction levels with current waste management systems set a standard against which the reception of Smart Bins can be measured, relevant for assessing potential social benefits (RO3) and stakeholder contentment (RO4). Perceived effectiveness of existing systems is key for RO2, where the feasibility of new technologies is considered, and RO3, which focuses on quality-of-life impacts.

Limited IoT knowledge, suggested by a low mean response, might pose a challenge for the acceptance and effective use of Smart Bins, as highlighted in both the introductory objective (RO1) and stakeholder analysis (RO4). Responses suggest a desire for improvement through IoT technology, which is significant for practicality and social benefit considerations in RO2 and RO3, respectively. The compatibility of IoT-powered Smart Bins with the unique demographics of Stirling is crucial for an efficient adoption (RO2) and fits within the Technology Acceptance Model's framework for compatibility (RO4).

A general willingness to adopt new technologies aligns with RO4's objective of evaluating stakeholder views, while beliefs about improved cleanliness through IoT technology directly address the social benefits targeted in RO3. The perceived ease of use and effectiveness of IoT technologies are central to their acceptance (RO4) and directly affect the actionable recommendations for stakeholders (RO5). The high willingness to use such technologies is favourable to the potential adoption of IoT powered smart bins, a key focus in RO4.

Although some concerns and challenges are noted, their low levels suggest they might not be significant barriers to adoption, offering valuable insights for understanding stakeholder apprehensions and planning for implementation (RO4 and RO5). In summary, the variables measured not only reflect on the current state of waste management but also offer insights towards the successful integration of Smart Bins into Stirling's urban landscape.

Tests of Normality

	What_Is_Your_Age	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Iot_Knowledge	18-24	,393	43	<,001	,621	43	<,001
	25-34	,374	28	<,001	,631	28	<,001
	35-44	,416	26	<,001	,604	26	<,001
	45-54	,398	16	<,001	,621	16	<,001
	55-64	,524	10	<,001	,366	10	<,001
	65+	.	6	.	.	6	.
Improve_Cleanliness_1to5	18-24	,266	43	<,001	,833	43	<,001
	25-34	,318	28	<,001	,779	28	<,001
	35-44	,237	26	<,001	,806	26	<,001
	45-54	,366	16	<,001	,638	16	<,001
	55-64	,324	10	,004	,794	10	,012
	65+	,333	6	,036	,827	6	,101
Wilingness_to_use_1to5	18-24	,309	43	<,001	,754	43	<,001
	25-34	,273	28	<,001	,744	28	<,001
	35-44	,376	26	<,001	,693	26	<,001
	45-54	,281	16	,001	,702	16	<,001
	55-64	,416	10	<,001	,650	10	<,001
	65+	,407	6	,002	,640	6	,001
Technology_Effectiveness_1to5	18-24	,263	43	<,001	,861	43	<,001
	25-34	,210	28	,003	,808	28	<,001
	35-44	,229	26	,001	,861	26	,002
	45-54	,313	16	<,001	,787	16	,002
	55-64	,254	10	,067	,833	10	,036
	65+	,293	6	,117	,915	6	,473
Ease_of_Use_1to5	18-24	,229	43	<,001	,862	43	<,001
	25-34	,229	28	<,001	,862	28	,002
	35-44	,297	26	<,001	,841	26	<,001
	45-54	,250	16	,009	,859	16	,019
	55-64	,245	10	,091	,820	10	,025
	65+	,209	6	,200*	,907	6	,415

Figure 4.2: *Tests of Normality*

The normality tests conducted provide insights into the distribution of respondent data across age groups for various variables pertinent to the research objectives.

For the variable 'IoT_Knowledge', both tests indicate statistical significance ($p < .001$) across all age categories, suggesting that the data does not follow a normal distribution. This is crucial for research objectives 1 (RO1) and 4 (RO4) as it may imply a non-uniform understanding of IoT, which could influence the perceived effectiveness and acceptance of Smart Bins.

'Improve_Cleanliness_1to5' also shows significant results ($p < .001$) in younger age groups but non-significant ($p > .05$) in the 55-64 bracket according to Shapiro-Wilk, suggesting a normal distribution only in this age category. For RO3, which looks at social benefits, this could mean that older demographics may have a consistent opinion on cleanliness improvements with Smart Bins, whereas younger groups' views are more varied.

'Willingness_to_use_1to5' displays a consistent rejection of normality across all ages ($p < .001$). This uniformity in non-normal distribution informs RO4, indicating that willingness to use Smart Bins may vary significantly within age groups, a factor for stakeholders to consider when planning engagement strategies.

The 'Technology_Effectiveness_1to5' and 'Ease_of_Use_1to5' variables follow a similar pattern of non-normal distribution in most age groups ($p < .001$), except for the oldest age group in 'Technology_Effectiveness_1to5', which shows a p-value of .117, suggesting a normal distribution. This finding may impact RO3 and RO4 as it suggests that older respondents could have a more uniform perception of technology effectiveness, potentially affecting adoption rates.

These deviations from normality imply that non-parametric methods may be more appropriate for subsequent analyses and that age-specific strategies may be necessary to address the diverse perceptions and acceptance levels revealed by the data, directly aligning with the approach required by the research objectives.

4.2.1 Regression Analyses

The following regression analyses have been carried out to determine relationships between dependent and independent variables as well as finding trends to forecast future outcomes for adoption.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,121[a]	,015	,007	,486

a. Predictors: (Constant), What_Is_Your_Age

b. Dependent Variable: Iot_Knowledge

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,445	1	,445	1,889	,172[b]
	Residual	29,942	127	,236		
	Total	30,388	128			

a. Dependent Variable: Iot_Knowledge

b. Predictors: (Constant), What_Is_Your_Age

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1,481	,085		17,451	<,001
	What_Is_Your_Age	-,040	,029	-,121	-1,374	,172

a. Dependent Variable: Iot_Knowledge

Figure 4.3: *Regression Analysis - Age and IoT Knowledge*

The data presented summarizes the output of a regression analysis examining the relationship between age and knowledge about the Internet of Things (IoT). The model summary indicates a weak correlation (R = .121) between the variables, with an R Square value of .015, meaning that age only explains 1.5% of the variance in IoT knowledge.

No statistical significance was found in the regression model between IoT knowledge and age (df(129) = 1.889, p = .172), this output suggests that age does not have a significant effect on IoT knowledge in this regression model.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,043[a]	,002	-,006	,703

a. Predictors: (Constant), What_Is_Your_Age

b. Dependent Variable: Wilingness_to_use_1to5

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,116	1	,116	,235	,629[b]
	Residual	62,721	127	,494		
	Total	62,837	128			

a. Dependent Variable: Wilingness_to_use_1to5

b. Predictors: (Constant), What_Is_Your_Age

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4,344	,123		35,376	<,001
	What_Is_Your_Age	,020	,042	,043	,485	,629

a. Dependent Variable: Wilingness_to_use_1to5

Figure 4.4: *Regression Analysis - Age and Willingness to Use*

The data presented summarizes the output of a regression analysis examining the relationship between age and willingness to use a certain technology (represented in the data as 'Willingness_to_use_1to5'). The model summary indicates a very weak correlation (R = .043) between the variables, with an R Square value of .002, meaning that age only explains 0.2% of the variance in willingness to use the technology.

Non-statistical significance was found in the regression model between willingness to use the technology and age (df(1, 127) = .235, p = .629). This output suggests that age does not have a significant effect on the willingness to use the technology in this regression model.

4.2.2 Correlations Analysis

The following correlation analysis has been carried out to understand the strength of the relationship between variables as well as identifying the variables that might be suitable for further testing.

Correlations

			Age	Improvement_3to5	Iot_Knowledge	Compatibility_3to5	Willingness_3to5	Ease_of_Use_3to5	Technology_Effectiveness_3to5	Wilingness_to_use_3to5
Spearman's rho	Age	Correlation Coefficient	1.000	.076	-.182*	-.067	.007	-.064	.088	.071
		Sig. (2-tailed)	.	.389	.039	.451	.935	.474	.320	.421
		N	129	129	129	129	129	129	129	129
	Improvement_3to5	Correlation Coefficient	.076	1.000	.066	.090	.159	.059	.073	.020
		Sig. (2-tailed)	.389	.	.457	.311	.072	.508	.412	.818
		N	129	129	129	129	129	129	129	129
	Iot_Knowledge	Correlation Coefficient	-.182*	.066	1.000	.170	.002	.033	-.098	.017
		Sig. (2-tailed)	.039	.457	.	.054	.981	.707	.270	.847
		N	129	129	129	129	129	129	129	129
	Compatibility_3to5	Correlation Coefficient	-.067	.090	.170	1.000	.040	-.006	.072	.027
		Sig. (2-tailed)	.451	.311	.054	.	.654	.948	.417	.763
		N	129	129	129	129	129	129	129	129
	Willingness_3to5	Correlation Coefficient	.007	.159	.002	.040	1.000	-.094	-.052	.108
		Sig. (2-tailed)	.935	.072	.981	.654	.	.288	.561	.222
		N	129	129	129	129	129	129	129	129
	Ease_of_Use_3to5	Correlation Coefficient	-.064	.059	.033	-.006	-.094	1.000	.347**	.239**
		Sig. (2-tailed)	.474	.508	.707	.948	.288	.	<.001	.006
		N	129	129	129	129	129	129	129	129
	Technology_Effectiveness_3to5	Correlation Coefficient	.088	.073	-.098	.072	-.052	.347**	1.000	.161
		Sig. (2-tailed)	.320	.412	.270	.417	.561	<.001	.	.069
		N	129	129	129	129	129	129	129	129
	Wilingness_to_use_3to5	Correlation Coefficient	.071	.020	.017	.027	.108	.239**	.161	1.000
		Sig. (2-tailed)	.421	.818	.847	.763	.222	.006	.069	.
		N	129	129	129	129	129	129	129	129

Figure 4.5: *Correlation Analysis*

The collected data was highly detailed, but for the chi-square test to generate valid results, it was necessary to consolidate the five satisfaction categories into three and combine the six age groups into two, these tests can be found in the appendices section as the Chi-square test did not generate statistically significant outputs. This adjustment was required as the expected count in some cells fell below the threshold of 5, which could compromise the test's validity.

The provided correlation analysis primarily employs Spearman's rho to measure the strength and direction of associations between variables related to smart city technology acceptance. The significance levels (two-tailed) are highlighted to identify statistically significant correlations, typically using a threshold of $p < 0.05$ which have been circled in the table above.

IoT Knowledge negatively correlates with Age (rho = -0.182, $p < 0.05$), indicating that as age increases, IoT knowledge decreases, which is significant for research objectives 1 (RO1) and (RO4) as it could imply that younger stakeholders may be more receptive to adopting Smart Bins.

Ease of Use shows a significant positive correlation with Technology Effectiveness (rho = 0.347, $p < 0.001$) and Willingness to Use (rho = 0.239, $p < 0.05$). This underlines that ease of use is a strong predictor of perceived effectiveness and willingness to engage with Smart Bins, directly aligning with research objectives 3 (RO3) and 4 (RO4) that address social benefits and user acceptance within the Technology Acceptance Model.

The significance of these correlations informs stakeholders about which demographic groups and perceptions need to be targeted in order to increase the likelihood of successful implementation of IoT solutions in urban waste management. These results suggest focusing on usability enhancements to improve overall technology acceptance, crucial for the development and deployment of Smart Bins in line with the research objectives.

4.2.3 Frequency Tables

Waste_Management_Satisfaction

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not at all	3	2,3	2,3	2,3
	Barely	37	28,7	28,7	31,0
	Average	57	44,2	44,2	75,2
	Very	28	21,7	21,7	96,9
	Very Much	4	3,1	3,1	100,0
	Total	129	100,0	100,0	

Figure 4.6: *Frequency Table - Satisfaction with Current Waste Management System*

Respondents' satisfaction with waste management in Stirling is categorized and presented as follows: 2.3% are 'Not at all' satisfied, 28.7% are 'Barely' satisfied, the largest group of 44.2% find it 'Average', 21.7% are 'Very' satisfied, and 3.1% are 'Very Much' satisfied. Cumulatively, 31% of the respondents report below-average satisfaction, and 69.9% report average or higher satisfaction.

Improvement_1to5

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	,8	,8	,8
	2	4	3,1	3,1	3,9
	3	33	25,6	25,6	29,5
	4	57	44,2	44,2	73,6
	5	34	26,4	26,4	100,0
	Total	129	100,0	100,0	

Figure 4.7: *Frequency Table - Improvement of Waste Management with IoT Powered smart bins*

Regarding the perceived improvement attributed to a service or product, rated on a scale from 1 to 5, the data reveals that 0.8% rated it as 1 (least improvement), 3.1% as 2, 25.6% as 3, 44.2% as 4, and 26.4% as 5 (most improvement). The cumulative percent indicates that 29.5% of respondents rated the improvement as 3 or lower, whereas 70.5% rated it as 4 or higher, showing a tendency towards a positive perception of potential improvement.

Compatibility_1to5

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	2	1,6	1,6	1,6
	2	5	3,9	3,9	5,4
	3	31	24,0	24,0	29,5
	4	63	48,8	48,8	78,3
	5	28	21,7	21,7	100,0
	Total	129	100,0	100,0	

Figure 4.8: *Frequency Table - Compatibility with Stirling Residents*

Participants rated compatibility on a scale of 1 to 5. The responses are distributed with 1.6% rating compatibility as 1, 3.9% as 2, 24% as 3, 48.8% as 4, and 21.7% as 5. The cumulative percent shows an increase across the scale, with a significant number of respondents (70%) rating the compatibility of potential IoT powered Smart Bins with Stirling residents as 4 or above.

Willingness_1to5

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	2	1,6	1,6	1,6
	3	22	17,1	17,1	18,6
	4	57	44,2	44,2	62,8
	5	48	37,2	37,2	100,0
	Total	129	100,0	100,0	

Figure 4.9: *Frequency Table - Willingness to Adopt*

In assessing willingness to adopt, the frequencies are as follows: 1.6% of respondents are rated at 2, 17.1% at 3, 44.2% at 4, and the highest proportion, 37.2%, at 5. The cumulative percentage increases with the scale, indicating a high overall willingness to use IoT powered smart bins in Stirling.

Wilingness_to_use_1to5

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	2	1,6	1,6	1,6
	3	10	7,8	7,8	9,3
	4	52	40,3	40,3	49,6
	5	65	50,4	50,4	100,0
	Total	129	100,0	100,0	

Figure 4.10: *Frequency Table - Willingness to Use*

The frequency distribution for willingness to use, rated from 2 to 5, is presented as follows: 1.6% of participants indicated a rating of 2, 7.8% a rating of 3, the largest group of 40.3% gave a rating of 4, and 50.4% expressed the highest willingness with a rating of 5. Cumulatively, 90.7% of respondents indicated a willingness rating of 3 or above, demonstrating a high overall willingness to use IoT powered smart bins among participants.

Challenges

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	100	77,5	77,5	77,5
	Yes	29	22,5	22,5	100,0
	Total	129	100,0	100,0	

Figure 4.11: *Frequency Table – Challenges*

The distribution of responses concerning potential challenges posed by IoT-powered smart bins for Stirling residents shows that 77.5% of participants reported 'No' challenges, suggesting a relative ease or absence of significant issues with the adoption or usage of such technology. Conversely, 22.5% of the respondents acknowledged facing 'Yes' challenges, indicating that a minority believe there are difficulties which may need to be addressed to create a positive user experience and technology acceptance. The cumulative percentage reflects the sum of respondents, underlining that the majority of residents did not encounter notable challenges.

Concerns

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	99	76,7	76,7	76,7
	Yes	30	23,3	23,3	100,0
	Total	129	100,0	100,0	

Figure 4.12: *Frequency Table - Concerns*

The frequency table for concerns shows that 76.7% of respondents reported 'No' concerns, while 23.3% reported 'Yes' to having concerns. This indicates a majority of the sample does not have concerns regarding the adoption of IoT powered smart bins in Stirling, with the cumulative percent mirroring the valid percent due to the binary nature of the response option.

6. Discussion

6.1 Introduction

The concept of a smart city as outlined in this study is to harnesses technology and data in order to improve the efficiency and quality of urban services, including waste management which has been the main topic of this research. This study focuses on Stirling, exploring the feasibility and community acceptance of integrating IoT powered smart bins. Despite the global shift towards smart cities primarily in larger urban centres, this research investigates the practicality and potential social implications of such initiatives in smaller urban environments such as Stirling. The following section will consider the data analysis in Chapter 4 and will discuss the key findings within the data gathered. The discussion section is structured to address each research objective, by categorizing findings under corresponding points.

6.2 Key Findings

RO 1: Understanding Smart City and Its Association with Urban Environments

As discussed in Chapter 1, smart cities utilise digital technology to enhance performance and well-being, to reduce costs and resource consumption, and to engage more effectively with citizens. The findings within the data analysis suggest that while the smart city concept is often associated with larger urban environments, smaller towns such as Stirling have unique opportunities to leverage technology for sustainable development, including IoT for waste management. The findings that outline these opportunities include the general openness across age groups towards smart technology, the positive perception of technology's effectiveness, a high overall willingness to adopt IoT-powered smart bins, and a majority of respondents having no significant challenges or concerns with their implementation, these findings can be seen in the Frequency Tables in section 4.2.3. These insights collectively point to a receptive community attitude towards adopting smart waste management solutions, demonstrating Stirling's potential to embrace smart city initiatives traditionally seen in larger urban settings.

RO 2: Practicality of Implementing Smart Bins in Stirling

The data analysis, including both regression and cross-tabulation analyses reveal that age does not directly influence IoT knowledge or the willingness to interact with smart technologies . This trend suggests a general readiness among different age groups to adopt smart bins.

The willingness to adopt provides a favourable starting point for smart city initiatives, potentially easing the adoption of innovative waste management solutions.

However, the findings reveal only very weak correlations between age and critical perceptions such as perceived technology effectiveness and ease of use [Figure 4.5]. This detail highlights how improvement is necessary to cultivate technology utilisation comfort and understanding, signalling the need for educational programs. Such initiatives should aim not only to strengthen community understanding and acceptance but also to bridge perceptual gaps, ensuring that all community members, regardless of age, can fully appreciate the benefits and functionalities of smart waste management systems. By addressing these educational needs, Stirling can create a more inclusive environment that is ready to support and benefit from smart city technologies, ensuring no resident feels left behind in the transition to more sustainable and efficient urban living.

The findings from this research can be integrated within the framework of the Technology Acceptance Model (TAM). As previously mentioned, Sepasgozar et al., (2019) suggest that two primary factors, perceived usefulness, and perceived ease of use, determine an individual's intention to use a technology and their actual use of it. The strong community inclination towards adopting smart waste management solutions in Stirling, as evidenced by the positive perceptions of technology's effectiveness (perceived usefulness) and operational simplicity (perceived ease of use), underscores the applicability of the TAM in understanding the factors driving the acceptance of smart city technologies. The below Figure [6.1] represents the TAM model and it has been adapted with the symbol + to represent the positive attitudes from survey respondents, it demonstrates how the external stimulus (functioning IoT powered smart bins) has a direct effect on cognitive response (perceived usefulness and ease of use) which in turn influences the affective and behavioural response of those utilising smart technology.

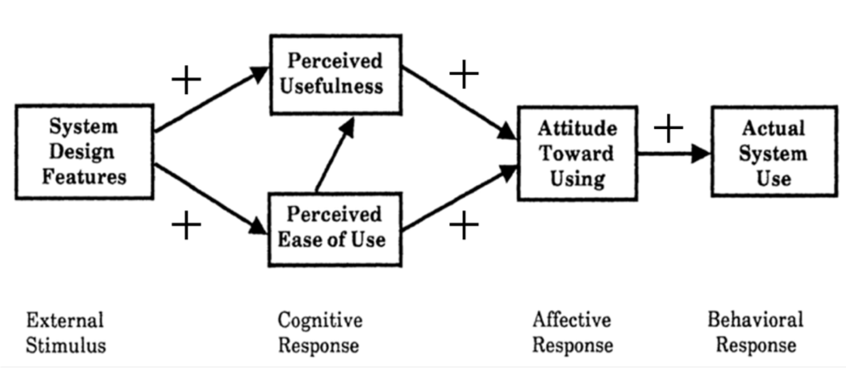


Figure 6.1: *TAM Model Adapted with Findings* ***Source:*** *Author*

RO 3: Potential Social Benefits or Drawbacks

Significant correlations were found within the data analysis, specifically in the Spearman's rho correlation coefficients section, illustrating a strong link between perceptions of technology effectiveness, ease of use, and the willingness to use the technology. This data suggests a clear community inclination: if smart bins are recognized as both effective in their function and user-friendly, they are more likely to gain widespread support within Stirling. The correlations, with coefficients indicating moderate positive relationships (e.g., ease of use and technology effectiveness ($rho = .347$, $p < .001$) [Figure 4.5], highlight the community's readiness to embrace smart waste management solutions, given their perceived benefits and operational simplicity.

Moreover, the majority of respondents, as shown in the frequency tables, anticipate no significant challenges or concerns with the adoption of smart bins, indicating a broadly positive social reception. This optimism is reflected in the 77.5% of participants reporting 'No' challenges and 76.7% expressing 'No' concerns regarding the integration of smart bin technology [Figure 4.11 and 4.12]. Such findings point towards a general consensus towards transitioning to smart waste management systems.

However, it's crucial to address the uncertainties held by a minority of the study's participants, which were evidenced in the same analysis concerning challenges and concerns (22.5% acknowledging 'Yes' challenges and 23.3% reporting 'Yes' to having concerns) [Figure 4.11 and 4.12]. These apprehensions bring to light areas requiring careful consideration, such as mitigating any digital gap that may prevent equal access to the benefits of this technology, the comments given by respondents regarding this can be found in Figure 6.2. Addressing these potential drawbacks is essential for creating an inclusive environment where the advantages of smart waste management systems are accessible to all community members.

Concerns with Smart Bins Implementation
These bins are very smart in their ability to tell us when they are full. However, I do not believe there is much use for them considering the cost of production.
People that like to damage the existing bins. My concern is that people would do the same to these.
Maintaining them and keeping them working the way they should become more hassle than they're worth.
Stirling is not a big city so it could be too expensive to support.
Learning how to correctly use especially for elders.
I have my doubts on everyone living in Stirling being able to adapt to this new technology. There are a lot of older people who might have a hard time with the change. The youth living here can be careless and destructive.

Figure 6.2: *Survey Respondents Concerns Comments* ***Source:*** *Author*

RO 4: Stakeholder Views on Smart Waste Management Systems

The survey indicates strong support for IoT-powered smart bins among Stirling's stakeholders, highlighting a crucial step towards advancing smart waste management initiatives. Engaging stakeholders effectively is essential for adapting the implementation to the community's specific needs and preferences. By integrating community feedback, the initiative will better align with stakeholder expectations, encouraging a sense of involvement and commitment to the success of the smart bin project.

Moreover, it's clear that further investigation is necessary to include all stakeholders identified in the stakeholder analysis [Figure 8]. This comprehensive inclusion will ensure that the project's planning and execution consider the full spectrum of community insights and requirements, reinforcing the project's foundation and increasing its likelihood of success. Prioritizing clear communication and stakeholder engagement will facilitate the process for Stirling to establish a supportive framework for innovative and sustainable urban waste management solutions.

RO 5: Recommendations for Stakeholders

Based on the analysis, the following recommendations are made for local government and stakeholders:

- **Educational Initiatives**: Develop comprehensive educational campaigns to increase awareness and understanding of smart waste management technologies.
- **Pilot Programs**: Implement pilot projects to assess the technology's effectiveness and gather community feedback before full-scale deployment.
- **Stakeholder Engagement**: Continuously engage with residents, businesses, and community organizations to incorporate their input and address concerns.
- **Accessibility and Inclusion**: Ensure the smart bin system is accessible and user-friendly for all demographics, mitigating the risk of a digital divide.
- **Continuous Monitoring**: Establish a framework for ongoing evaluation of the system's performance, community satisfaction, and environmental impact.

6.3 Discussion Conclusion

This study underscores the significant potential for Stirling to lead by example in the adoption of smart waste management technologies within smaller urban settings. The findings from the investigation reveal a strong community readiness to embrace IoT-powered smart bins, driven by a general openness towards smart technology, positive perceptions of its effectiveness, and the practicality of its implementation across diverse age groups. The data highlights the need for thorough educational campaigns to close knowledge gaps and achieve widespread understanding and acceptance in the community.

The estimated social benefits, including enhanced urban cleanliness and more efficient waste management, coupled with minimal concerns or challenges reported by the majority, highlight the community's optimism towards this innovative approach. Nonetheless, addressing the concerns of a minority and ensuring inclusiveness in technology access and privacy considerations remains imperative to adopt a truly inclusive smart city environment.

The Technology Acceptance Model (TAM) provides a robust theoretical framework for interpreting the findings of this research, offering insights into the dynamics of smart technology adoption in small urban settings. By highlighting the critical roles of perceived usefulness and ease of use, along with the importance of a positive attitude and social influence, the TAM reinforces the recommendations made for enhancing community engagement, educational outreach, and stakeholder involvement in Stirling's journey towards smart waste management. The study's consistency with TAM highlights smart bins as a viable step towards a sustainable city.

Lastly, engaging a broader spectrum of stakeholders and integrating their feedback is essential for refining the implementation process and maximizing the project's impact. This study lays the groundwork for Stirling to advance towards becoming a smarter, more sustainable city, advocating for the strategic deployment of smart waste management solutions that cater to the needs of its residents. The recommendations provided aim to guide local government and stakeholders in navigating the challenges and leveraging the opportunities that come with these initiatives, emphasizing the importance of continuous engagement, accessibility, and the monitoring of progress towards achieving a cleaner, more efficient urban environment.

8. Conclusion

This research investigated the feasibility and implications of integrating smart city technologies, particularly IoT-powered smart bins, in the smaller urban setting of Stirling. The study examined technological, and societal aspects of such implementations in a context defined by specific size, demographics, and community dynamics. It provides insights into the potential of smaller cities in contributing to the smart urban development narrative, challenging the notion that smart cities are exclusive to larger metropolitan areas.

The research identified the adaptability and feasibility of smart city technologies in smaller urban areas such as Stirling. Despite its scale, Stirling demonstrated a capacity to adopt smart innovations, attributed to both technological infrastructure and societal willingness. The study found significant opportunities for Stirling to lead in environmental sustainability and efficient waste management, contributing to smart city evolution.

The societal impacts of deploying smart technologies in Stirling were explored, revealing a generally positive community response to improved waste management systems. The research emphasized the need for inclusive strategies to address challenges related to accessibility, and digital divides, aiming to enhance quality of life for all residents through smart urban living transitions.

Community engagement and stakeholder involvement were highlighted as vital to the smart city transition process. The findings stressed the importance of diverse perspectives and collaboration in planning and implementation, enhancing technology adoption success and strengthening social consistency through shared commitment to sustainable development.

The study outlines recommendations for Stirling and similar urban areas on embracing smart city principles, including education, and continuous evaluation. It advocates for an adaptive approach to address emerging challenges and align smart initiatives with community needs and aspirations.

This research contributes to the smart city discourse by including smaller urban areas in the discussion, offering scalable and adaptable insights. By demonstrating Stirling's integration of smart technologies, it challenges traditional perceptions and underscores the role of smaller cities in sustainable, efficient, and inclusive urban development. The findings encourage the development of urban living, highlighting the importance of community-centric approaches and stakeholder engagement in the smart city revolution.

9. References

- Adetimirin, A., 2015. An empirical study of online discussion forums by library and information science postgraduate students using technology acceptance model 3. *Journal of Information Technology Education. Research*, *14*, p.257.
- Albino et al., (2015). Smart Cities: Definitions, Dimensions, Performance, and Initiatives. *Journal of Urban Technology*, [online] 22(1), pp.3–21.
- Anagnostopoulos et al., 2015. Assessing dynamic models for high priority waste collection in smart cities. *Journal of Systems and Software*, *110*, pp.178-192.
- Angelidou, M. (2015). Smart cities: a Conjuncture of Four Forces. *Cities*, 47, pp.95–106.
- Ashton, K., 2009. That 'internet of things' thing. *RFID journal*, *22*(7), pp.97-114.
- Bassi et al., 2013. *Enabling Things to Talk: Designing IoT solutions with theIoT Architectural Reference Model* (p. 379). Springer Nature.
- Bibri, S.E. (2018). A Foundational Framework for Smart Sustainable City development: Theoretical, disciplinary, and Discursive Dimensions and Their Synergies. *Sustainable Cities and Society*, 38(38), pp.758–794.
- Bokolo, A.J. (2023). Examining the Adoption of Sustainable eMobility-Sharing in Smart Communities: Diffusion of Innovation Theory Perspective. *Smart Cities*, [online] 6(4), pp.2057–2080.
- Boughzala, I., 2014. How generation Y perceives social networking applications in corporate environments. In *Integrating Social Media into Business Practice, Applications, Management, and Models* (pp. 162-179). IGI Global.
- Brown et al.,(2020). UK Smart Cities Present and future: an Analysis of British Smart Cities through Current and Emerging Technologies and Practices. *Emerald Open Research*, 2, p.4.
- Chatman, E.A., 1986. Diffusion theory: A review and test of a conceptual model in information diffusion. *Journal of the American Society for Information Science*, *37*(6), pp.377-386.
- Chuttur, M., 2009. Overview of the technology acceptance model: Origins, developments, and future directions.
- Davis, F.D., 1985. *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation, Massachusetts Institute of Technology).
- Eaton, J. and Kortum, S., 1999. International technology diffusion: Theory and measurement. *International Economic Review*, *40*(3), pp.537-570.
- Georgiadis et al., (2021). Citizens' Perception of Smart Cities: a Case Study. *Applied Sciences*, [online] 11(6), p.2517.

- Gracias et al., 2023. Smart Cities—A Structured Literature Review. *Smart Cities*, *6*(4), pp.1719-1743.
- Hanlon, A. (2013). *What Is the Diffusion of Innovation model?* [online] Smart Insights. Available at: https://www.smartinsights.com/marketing-planning/marketing-models/diffusion-innovation-model/.
- Harrison, C. and Ian Abbott Donnelly (2011). A Theory of Smart Cities. 55(1).
- Hollands, R.G. (2008). Will the real smart city please stand up? *City*, [online] 12(3), pp.303–320.
- Hossein Motlagh, N., Mohammadrezaei, M., Hunt, J. and Zakeri, B., 2020. Internet of Things (IoT) and the energy sector. *Energies*, *13*(2), p.494.
- Javed et al., (2022). Future Smart Cities requirements, Emerging technologies, applications, challenges, and Future Aspects. *Cities*, 129(0), p.103794.
- Kim et al., (2022). 6LoWPAN over optical wireless communications for IPv6 transport in Internet of Things networks. *IEEE Wireless Communications Letters*, *11*(6), pp.1142-1145.
- Kim et al., 2017. Smart city and IoT. *Future Generation Computer Systems*, *76*, pp.159-162.
- Kontokosta, C.E. and Hong, B., 2021. Bias in smart city governance: How socio-spatial disparities in 311 complaint behavior impact the fairness of data-driven decisions. *Sustainable Cities and Society*, *64*, p.102503.
- Kramp, T., Van Kranenburg, R. and Lange, S., 2013. Introduction to the Internet of Things. *Enabling things to talk: Designing IoT solutions with the IoT architectural reference model*, pp.1-10.
- Kuziemski, M. and Misuraca, G. (2020). AI Governance in the Public sector: Three Tales from the Frontiers of Automated decision-making in Democratic Settings. *Telecommunications Policy*, 44(6), p.101976.
- Linstone, H.A. and Turoff, M. eds., 1975. *The Delphi Method (*pp. 3-12). Reading, MA: Addison-Wesley.
- Long, T.B., Blok, V. and Coninx, I., 2016. Barriers to the adoption and diffusion of technological innovations for climate-smart agriculture in Europe: evidence from the Netherlands, France, Switzerland, and Italy. *Journal of cleaner production*, *112*, pp.9-21.
- Madakam, S., Lake, V., Lake, V. and Lake, V., 2015. Internet of Things (IoT): A literature review. *Journal of Computer and Communications*, *3*(05), p.164.
- Malhotra, P., Singh, Y., Anand, P., Bangotra, D.K., Singh, P.K. and Hong, W.C., 2021. Internet of things: Evolution, concerns, and security challenges. *Sensors*, *21*(5), p.1809.
- Marangunić, N. and Granić, A., 2015. Technology acceptance model: a literature review from 1986 to 2013. *Universal access in the information society*, *14*, pp.81-95.
- Marsa-Maestre, I., Lopez-Carmona, M. A., Velasco, J. R., & Navarro, A. (2008). Mobile agents for service personalization in smart environments. *Journal of Networks*, *3*(5), 30-41.

- Mishra, N. and Pandya, S., 2021. Internet of things applications, security challenges, attacks, intrusion detection, and future visions: A systematic review. *IEEE Access*, *9*, pp.59353-59377.
- Nam, T. and Pardo, T.A. (2011). Conceptualizing smart city with dimensions of technology, people, and institutions. *Proceedings of the 12th Annual International Digital Government Research Conference on Digital Government Innovation in Challenging Times*.
- National Records of Scotland. www.nrscotland.gov.uk. (n.d.). *Stirling Council Area Profile*. [online] Available at: https://www.nrscotland.gov.uk/files/statistics/council-area-data-sheets/stirling-council-profile.html#pop_est_plots1. Last Accessed:31/10/23
- Nižetić, S., Šolić, P., Gonzalez-De, D.L.D.I. and Patrono, L., 2020. Internet of Things (IoT): Opportunities, issues and challenges towards a smart and sustainable future. *Journal of cleaner production*, *274*, p.122877.
- Rogers, E.M. (1962). *Diffusion of Innovations*. 5th ed. New York: Free Press.
- Rossi, U. (2015). The Variegated Economics and the Potential Politics of the Smart City. *Territory, Politics, Governance*, 4(3), pp.337–353.
- Roth, D., Montavont, J. and Noel, T., 2012, October. Performance evaluation of mobile ipv6 over 6lowpan. In *Proceedings of the 9th ACM symposium on performance evaluation of wireless ad hoc, sensor, and ubiquitous networks* (pp. 77-84).
- Sánchez-Corcuera, R., Nuñez-Marcos, A., Sesma-Solance, J., Bilbao-Jayo, A., Mulero, R., Zulaika, U., Azkune, G. and Almeida, A., 2019. Smart cities survey: Technologies, application domains and challenges for the cities of the future. *International Journal of Distributed Sensor Networks*, *15*(6), p.1550147719853984.
- Sepasgozar, S.M., Hawken, S., Sargolzaei, S. and Foroozanfa, M., 2019. Implementing citizen centric technology in developing smart cities: A model for predicting the acceptance of urban technologies. *Technological Forecasting and Social Change*, *142*, pp.105-116.
- Setiyani, L., Effendy, F. and Slamet, A.A., 2021. Using Technology Acceptance Model 3 (TAM 3) at selected private technical high school: google drive storage in e-learning. *Utamax: Journal of Ultimate Research and Trends in Education*, *3*(2), pp.80-89.
- Wani, T.A. and Ali, S.W. (2015). Innovation Diffusion Theory Review & Scope in the Study of Adoption of Smartphones in India. *Journal of General Management Research*, 3(2), pp.101–118.
- Yang, C., 2020. *Remapping Songdo: A genealogy of a smart city in South Korea* (Doctoral dissertation, University of Illinois at Urbana-Champaign).
- Zanella, A., Bui, N., Castellani, A., Vangelista, L. and Zorzi, M., 2014. Internet of things for smart cities. *IEEE Internet of Things journal*, *1*(1), pp.22-32.

- Zavratnik, V., Podjed, D., Trilar, J., Hlebec, N., Kos, A. and Stojmenova Duh, E., 2020. Sustainable and community-centred development of smart cities and villages. *Sustainability*, *12*(10), p.3961.

10. Appendices

Age * Wilingness_to_use_3to5 Crosstabulation

Count

		Wilingness_to_use_3to5			
		3	4	5	Total
Age	Under 26	11	49	58	118
	Over 26	1	3	7	11
Total		12	52	65	129

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	.927[a]	2	.629
Likelihood Ratio	.957	2	.620
Linear-by-Linear Association	.505	1	.477
N of Valid Cases	129		

a. 2 cells (33.3%) have expected count less than 5. The minimum expected count is 1.02.

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Interval by Interval	Pearson's R	.063	.089	.709	.479[c]
Ordinal by Ordinal	Spearman Correlation	.071	.088	.807	.421[c]
N of Valid Cases		129			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

Appendix 1: Age and Willingness to Use Cross Tabulation

Age * Willingness_3to5 Crosstabulation

Count

		Willingness_3to5			
		3	4	5	Total
Age	Under 26	21	54	43	118
	Over 26	3	3	5	11
Total		24	57	48	129

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	1.484[a]	2	.476
Likelihood Ratio	1.528	2	.466
Linear-by-Linear Association	.000	1	.984
N of Valid Cases	129		

a. 3 cells (50.0%) have expected count less than 5. The minimum expected count is 2.05.

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Interval by Interval	Pearson's R	-.002	.100	-.020	.984[c]
Ordinal by Ordinal	Spearman Correlation	.007	.099	.082	.935[c]
N of Valid Cases		129			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

Appendix 2: Age and Willingness to Adopt Cross Tabulation

Age * Ease_of_Use_3to5 Crosstabulation

Count

		Ease_of_Use_3to5			
		3	4	5	Total
Age	Under 26	32	56	30	118
	Over 26	4	5	2	11
Total		36	61	32	129

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	.529[a]	2	.767
Likelihood Ratio	.525	2	.769
Linear-by-Linear Association	.516	1	.473
N of Valid Cases	129		

a. 2 cells (33.3%) have expected count less than 5. The minimum expected count is 2.73.

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Interval by Interval	Pearson's R	-.063	.087	-.717	.475[c]
Ordinal by Ordinal	Spearman Correlation	-.064	.087	-.718	.474[c]
N of Valid Cases		129			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

Appendix 3: Age and Ease of Use Cross Tabulation

Age * Technology_Effectiveness_3to5 Crosstabulation

Count

		Technology_Effectiveness_3to5			Total
		3	4	5	
Age	Under 26	35	54	29	118
	Over 26	2	5	4	11
Total		37	59	33	129

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	1.009[a]	2	.604
Likelihood Ratio	1.015	2	.602
Linear-by-Linear Association	.998	1	.318
N of Valid Cases	129		

a. 2 cells (33.3%) have expected count less than 5. The minimum expected count is 2.81.

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Interval by Interval	Pearson's R	.088	.086	.999	.320[c]
Ordinal by Ordinal	Spearman Correlation	.088	.086	.998	.320[c]
N of Valid Cases		129			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

Appendix 4: Age and Technology Effectiveness Cross Tabulation

Age * Compatibility_3to5 Crosstabulation

Count

		Compatibility_3to5			
		3	4	5	Total
Age	Under 26	29	62	27	118
	Over 26	4	5	2	11
Total		33	67	29	129

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	.743[a]	2	.690
Likelihood Ratio	.695	2	.706
Linear-by-Linear Association	.566	1	.452
N of Valid Cases	129		

a. 2 cells (33.3%) have expected count less than 5. The minimum expected count is 2.47.

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Interval by Interval	Pearson's R	-.066	.091	-.751	.454[c]
Ordinal by Ordinal	Spearman Correlation	-.067	.091	-.757	.451[c]
N of Valid Cases		129			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

Appendix 5: Age and Compatibility of IoT powered Smart Bins with Stirling Residents Cross Tabulation

Age * Improvement_3to5 Crosstabulation

Count

		Improvement_3to5			Total
		3	4	5	
Age	Under 26	32	56	30	118
	Over 26	2	5	4	11
Total		34	61	34	129

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	.770[a]	2	.680
Likelihood Ratio	.760	2	.684
Linear-by-Linear Association	.748	1	.387
N of Valid Cases	129		

a. 2 cells (33.3%) have expected count less than 5. The minimum expected count is 2.90.

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Interval by Interval	Pearson's R	.076	.087	.864	.389[c]
Ordinal by Ordinal	Spearman Correlation	.076	.087	.864	.389[c]
N of Valid Cases		129			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

Appendix 6: Age and Expected Improvement with Smart Bins Implementation Cross Tabulation

Age * Effective Crosstabulation

Count

		Effective			
		Barely	Average	Very	Total
Age	Under 26	42	58	18	118
	Over 26	3	6	2	11
Total		45	64	20	129

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	.314[a]	2	.855
Likelihood Ratio	.325	2	.850
Linear-by-Linear Association	.271	1	.603
N of Valid Cases	129		

a. 2 cells (33.3%) have expected count less than 5. The minimum expected count is 1.71.

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Interval by Interval	Pearson's R	.046	.086	.519	.605[c]
Ordinal by Ordinal	Spearman Correlation	.047	.086	.535	.594[c]
N of Valid Cases		129			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

Appendix 7: Age and Effectiveness of Current Waste Management Systems Cross Tabulation

Age * Waste_Management_Satisfaction Crosstabulation

Count

		Waste_Management_Satisfaction			Total
		Barely	Average	Very	
Age	Under 26	37	54	27	118
	Over 26	5	5	1	11
Total		42	59	28	129

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	1.496[a]	2	.473
Likelihood Ratio	1.661	2	.436
Linear-by-Linear Association	1.463	1	.226
N of Valid Cases	129		

a. 2 cells (33.3%) have expected count less than 5. The minimum expected count is 2.39.

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Interval by Interval	Pearson's R	-.107	.079	-1.212	.228[c]
Ordinal by Ordinal	Spearman Correlation	-.106	.081	-1.203	.231[c]
N of Valid Cases		129			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

Appendix 8: Age and Satisfaction with Current Waste Management Systems Cross Tabulation