CHARACTERISING SMART CITIES:

FORM, FUNCTION AND FEATURES

by

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Global urbanization trends have continued to skyrocket the past several decades and are projected to continue. More than ever before, more people are electing to live in cities which poses unprecedented challenges for city stakeholders in addressing the quality of life of city inhabitants. Frameworks for a sustainable city development is needed to address the many challenges cities around the world are facing today. Smart City initiatives have emerged as an alternative means to tackle sustainable city development challenges. Due to the nature of smart city objectives being highly local and even regional, different cities require different "smart" solutions. These differences make it difficult to set a singular definition of what a "smart" city is. This thesis seeks to record the progression of smart city definitions over time and to offer a working definition towards a universal definition of smart cities. In addition, the data analysis portion of this work seeks will examine the relationships between several smart city factors and their significance in reducing city generated greenhouse gas emissions. Furthermore, this research will quantify the extent by which these smart city factors effectively achieve the goals of smart cities. The findings of this research can be used by city stakeholders as a guide to prioritize smart city initiatives and efficiently allocate city resources in the most effective ways possible.

Chapter 1

INTRODUCTION

1.1 General

The 2018 World Urban Prospect Report produced by the United Nations Department of Economic and Social Affairs notes the world urban population has grown exponentially from 715 million in 1950 to 4.2 billion in 2018. The report estimates about 68% of the world population is projected to live in urban areas by 2050 (see Figure 1). This is due to an overall growth of world population coupled with a general increase in the number of people electing to live in urban environments rather than rural areas. As a result, urban environments will see an additional 2.5 billion dwellers within this period. Currently, North America, Latin America and the Caribbean, Europe and Oceania account for the world's highest urbanized areas with urbanization rate of 82%, 81%, 74% and 68% respectively. Close to 90% of the world urbanization increase is expected to take place in Asia and Africa, as they account for the least urbanized regions of the world with urbanization rate of 50% and 43% respectively (UNDESA, 2018).

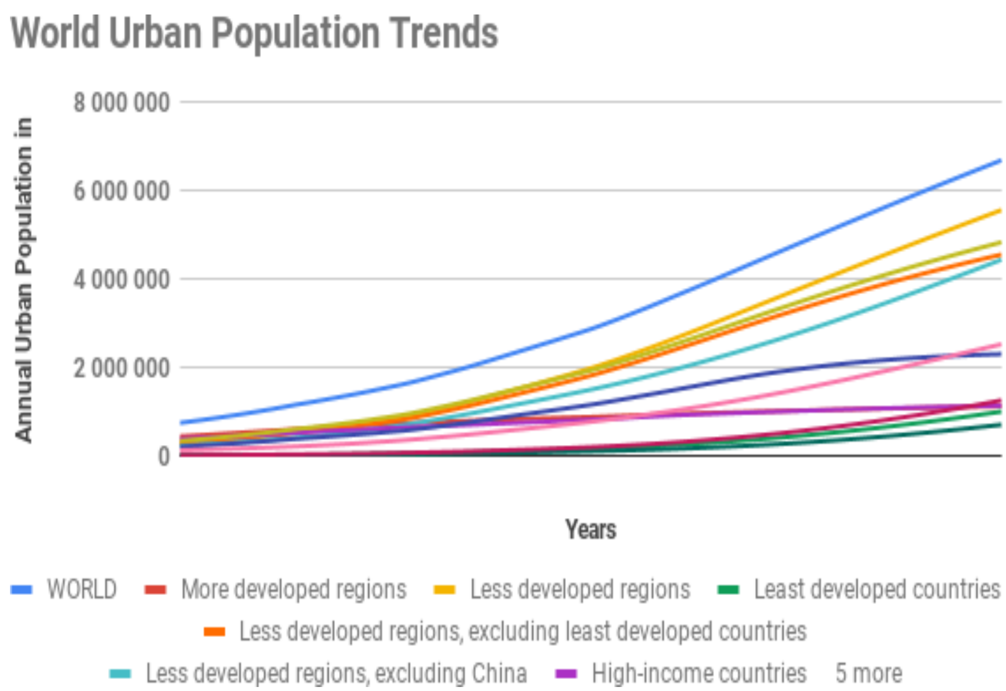

Figure 1 Global Urbanization Trends by 2050 (UN)

1.2 Problem Statement

Cities around the world are looking for effective ways to address the adverse effects of increasing global urbanization. The pressure is on city stakeholder such as city authorities, citizens, research institutions, businesses and many others to develop an appropriate framework for sustainable urban development. In the past two decades, smart city concepts powered by the Internet of Things (IoT) and big data have emerged as a means to address various elements of increasing global urbanization complexities. The sustainability of the projected megacities of the future relies on the level of success achieved meeting the challenges of increasing urbanization. However, because all cities are not similar in size, development, and population make-up, smart city solutions have varied in approach and capacity. Therefore, there is a need to assess the impact of the "smartness" of a city in tacking urbanization issues such as increasing carbon dioxide (CO2) emissions.

1.3 Objectives of Research

1.3.1 Main Objective

The main objective of this research is to measure the viability of Smart City Concepts as a means for sustainable urban development and reducing city generated greenhouse gas emission. This will be achieved through the sub-objectives below.

1.3.2 Sub-Objectives

1. To conduct a thorough literature review of smart city definitions and interpretations.
2. To examine the infrastructure and the processes that enable smart city functions.
3. To measure the effectiveness of smart city initiatives through selected examples of smart city initiatives in various urban environments.

4. To evaluate various smart city factors targeted in smart city initiatives in reducing city generated greenhouse gas emissions.

1.4 Research Framework

The research framework of this thesis entails:

A. Assessing urban population growth trends worldwide.

B. Developing a working definition of smart cities based on wholistic perspective from the literature.

C. Identify key components of smart city infrastructure and the Internet of Things (IoT).

D. Highlight selected examples of smart city deployments for sustainable development.

E. Analyze the relationship between Carbon Dioxide (CO_2) emission and "smartness of a city.

1.5 Organization of Thesis

The thesis has five chapters. Chapter 1 is the introductory chapter. It briefly introduces the research problem and the research plan. Chapter 2 presents a literature review of Smart City definitions and interpretations through a historical lens varying in context and application. Chapter 3 presents selected examples of Smart City deployments and examines the functions and effectiveness of those particular deployments. Chapter 4 analyzes CO_2 emissions per capita of ranked smart cities and develops insight into the relationship between a city's smartness and its levels of CO_2

emissions. Finally, chapter 5 outlines some key challenges and concerns for smart cities moving forward and presents best practices for city stakeholders such as planners, citizens and businesses.

Chapter 2

SMART CITY DEFINITIONS

2.1 Definitions

In recent decades smart cities have emerged as viable means to address increasing global urbanization. Many cities around the globe have looked to smart city concepts as a platform to develop a sustainable growth urban development framework. Ideas about the future of society, economy and urban settlement under the influence of advancing technology first appeared in 1850s, followed by conception of ideal city in the industrial era, 1898 Europe (Angelidou, 2015). In the early 1900s, the meaning of smart cities progressed to be understood as any technology-based innovation in the context of the urban environment, what later became coined as the “smart growth movement.” (Yigitcanlar & Kamruzzaman, 2018). The futurist movement of (1909-1016) and the Bauhaus movement of (1919-1932) propagated industrial era city concepts and envisioned the city as an efficient, fast-paced, highly industrialized and mechanized machines. Modern technology was the perceived as the driving force behind such ambitions. Increased population growth after World War II led to the concept of developing planned cities and suburbs of which the integration of technological advancement was a key component. (Angelidou, 2015). Over the years, various definitions have emerged focusing singular component of smart cities. Some of the prevailing terms of those interpretations include ubiquitous city, techno-centric city, creative city, sustainable city, resilient city, digital city, intelligent city and knowledge city (See Figure 2).

Figure 2 Smart City Prevailing Terms

After two decades since its surge in popularity, there is no universally agreed upon definition of a smart city (Yigitcanlar & Kamruzzaman, 2018) . The lack of a consensus definition for smart cities might be attributed to the varying contexts of cities and their urban environment challenges referring mainly to developing cities versus developed cities. A possible way of understanding the confusion around a one-definition fit all for smart cities, is examining the diffusion patterns of smart cities initiatives around the world. That is understanding the elements that facilitate or hinder the spread of smart city deployments around the world i.e. political, economic and cultural context issues (Neirotti, De Marco, Cagliano, Mangano, & Scorrano, 2014).

Closely looking at the literature for the past two decades we find a wide variety of interpretation of the definition of a smart city emphasizing different aspects and themes of a smart city. In 2000, scholars from the Brookhaven National Laboratory envisioned smart cities of the future being made possible by a bottoms-up approach of and urban environment design overhaul. In the vision, these scholars foresaw the future smart cities as one that will make use of advanced, integrated and interconnected cyber-physical systems that will optimize city resources to better serve the needs of its citizens. (Bowerman et al. 2000). By 2009, a more technology focus definition is offered imagining smart cities as a result of computing technologies to make critical infrastructure components more intelligent, interconnected and efficient (Washburn & Sindhu, 2009). Harrison et al. expands this technology driven view of smart cities to include social and business infrastructure to leverage collective intelligence of the city. This framework, they concede will allow cities to gather, integrate, analyze, optimize city operations (Harrison et al., 2010).

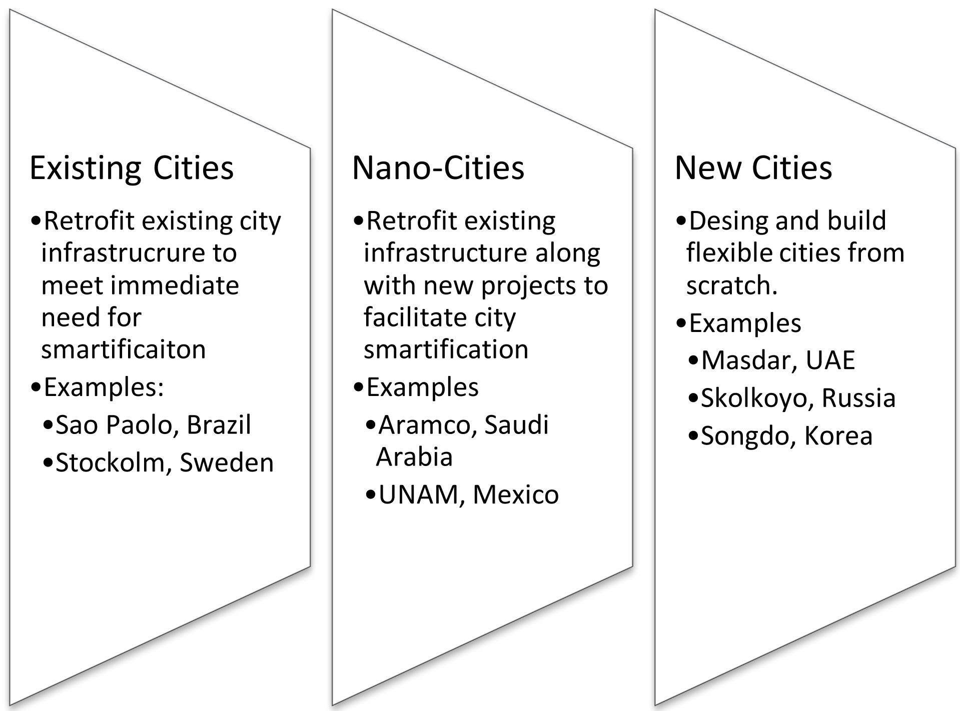

Figure 3 Stages of Smart City Development adopted from (Bélissent, 2010)

Skepticism grew over the overwhelming emphasis on technology as the defining element of smart cities. One view offered that the stress on technology as the identifier no longer suffices. Investments are need to be made in human and social capital along with physical infrastructure for urban life to thrive in a sustainable manner (Caragliu, del Bo, & Nijkamp, 2011). Thus, investments in the quality of life of urban citizens would attract knowledge workers to live and work in smart cities which is essential for sustained development and growth of smart cities (Thite, 2011). Nam and Pardo added city operational efficiency gains is not enough to identify the city as smart rather “a smart city should be treated as an organic whole, as a network, as a linked system” (Nam & Pardo, 2011).

Furthermore, the literature continues to broaden the spectrum of understanding of what smart cities stand for. Part of the framework of smart cities should include the importance of the development of urban policy to improve the quality of life all residents, in particular, the disadvantaged and the poor (Thuzar, 2012). Smart city initiatives should deliver through knowledge and creative strategies on a mix of investments in areas of human, infrastructure and social and entrepreneurial capital (Kourtit & Nijkamp, 2012). To do so, smart cities should represent a community of average technology size interconnected and sustainable, comfortable, attractive and secure (Lazaroiu & Roscia, 2012). Not absent from this is streamlining and automating the systems of smart cities to produce, discover and understand and provide solutions in real-time (Cretu, 2012). More recently, the ability of a city to actively generate smart ideas through city open data and or living labs with direct citizen input in the development of products and services has become a key determinant of the smartness of a city (Bakici, Almirall, & Wareham, 2013).

This particular interpretation of a smart city relies on building the learning capacity of citizens and seeks to extract creative and innovative ideas from people (Komninos, 2014). Japan on the other hand, views the smart cities as the fifth step in human development, hence the name society 5.0. This vision proposes a cyber- physical system that harness the power of technology to create a “Super Smart Society”. It aims to develop common platform technologies, services and systems for new market creation and transformation into a prosperous society by creating values through cyber-physical systems (Shiroishi, Uchiyama, & Suzuki, 2018). The Society 5.0 concept of smart cities builds upon the 17-goal framework set by the United Nations to guide sustainable development.

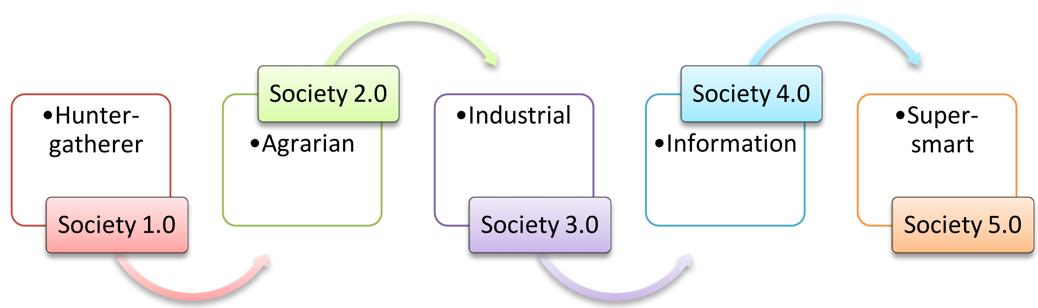

Figure 4 Japan's Interpretation of Societal Progression

The wide range of interpretations of what a smart city is can be categorized into three categories. One category focuses its attention on the implementation of Internet Communication Technologies (IoT) in the physical infrastructure of cities to create flexibilities and increase capacities in the operational systems and processes of a city. Some of the prevailing terminology in this category are ubiquitous city, digital city, and informational city along with other city infrastructure related technology advancements. The second category of definitions in the literature emphasizes on the enhancement of economic elements of a city. Under this category, a smart city is defined by the educational level of its citizens and the level of creative economic output that emerge from it. The prominent terminology in this category include intelligent city, knowledge city, creative city and innovative city. Lastly, closely related to the second category, the third category of definitions define smartness by the investments made in human capital. The emerging terminologies in this space include the learning city and human smart city. To put it all together, what is evident in the varying definitions of smart cities is that city infrastructures should be equipped with IoT technologies in order to sense and gather data to be analyzed and used to facilitate efficient and citizen centric decisions technological solutions (Marsal-Llacuna, Colomer-Llinàs, & Meléndez-Frigola,2015).

2.2 Smart City Elements

2.2.1 Governments

Governments provide vision and leadership for defining the specific application of the smart city strategy that will be implemented. They are responsible for seeking out funding whether on a local, state, or national level, from private partnerships with industry, or open source initiatives with citizens and competitions. The success of the smart city projects depends on the size of the project, its integration within the city, and the implementation. Smart city governments can be ranked based on the concepts of clarity of vision, leadership, budget, financial incentives, support programs, talentreadiness, people-centricity, innovation ecosystems, “smart” policies (i.e. data governance, IP protection, etc.), and track record of previous projects.

The number of smart city projects worldwide grows every year, but implementation varies greatly. The clustering of smart city projects based on scope, integration, and scale can be seen in Figure 5 (Eden Strategy Institute, 2018). Smart city planners must determine how many services and departments they want to involve in the plan (scope). The geographic region, population, or budgets (scale) are often constraints that planners do not have control over, but heavily influence the smart city strategy. Asian smart cities are generally on a larger scale than European and American cities. How the collected data is analyzed and put into actionable services determines if the project is successful (integration).

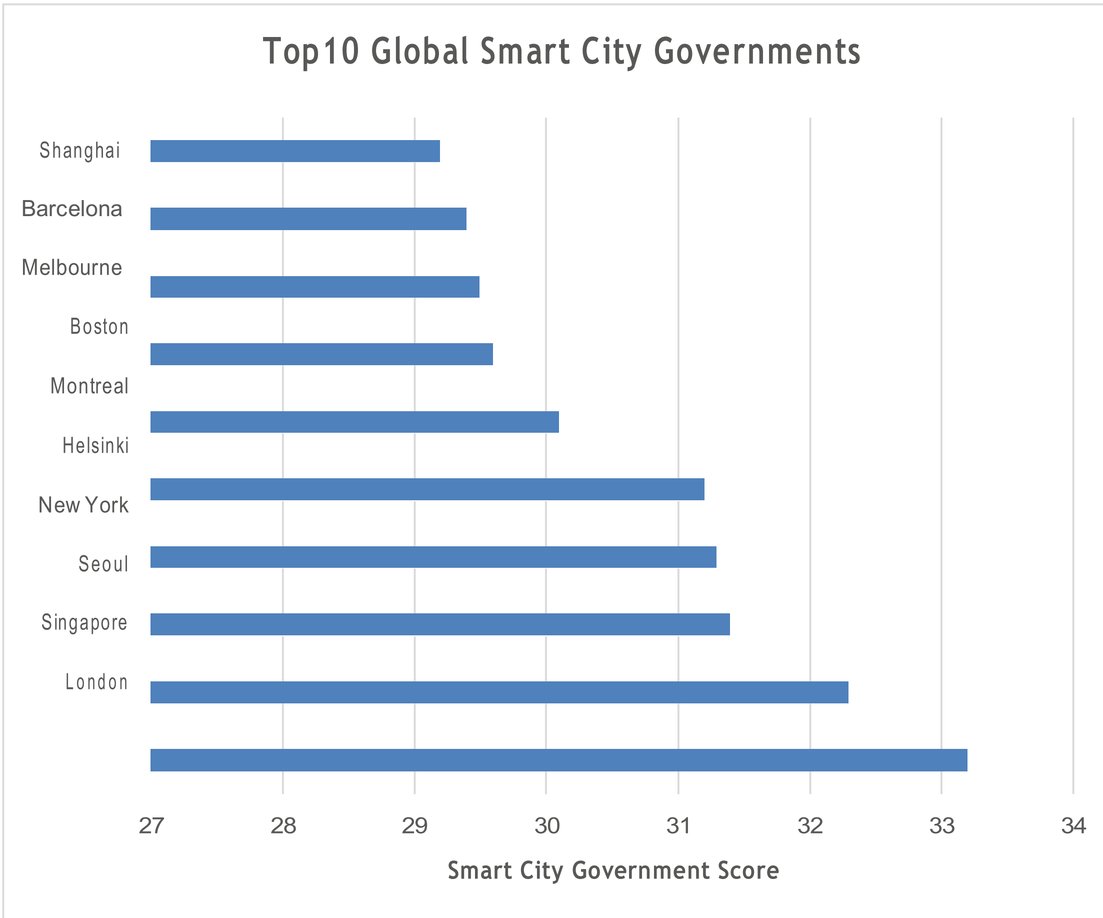

Figure 5 Global Smart City Rankings, adopted from Eden Strategy Institute, 2018

At the local level, smart city projects are mostly implemented on a city-wide basis in United States. City government officials decide whether to invest in smart technologies. While implementation of city-wide efforts is localized, there is significant investment in specific technological areas that help advance the development of smart technologies. For example, the Networking and Information Technology and Research Program funds academic, government, and private sectors to advance innovation.

At a regional level, The Chinese government engages in centralized planning and has invested heavily in moving from digital cities to smart cities. They are experimenting with hundreds of pilot smart cities as testing grounds for refining technological concepts in preparation for future upscaling. The government has also partnered with western organizations to launch China-EU Smart City Cooperation adding 15 pilot cities (Liu & Peng, 2014). The financial investment the Chinese government offers include funding for the underlying IT infrastructure.

2.2.2 Business and Technology

As cities aim to increase the IoT network of technology, businesses leverage their technological solutions to provide tools for smart cities. For example, in Stockholm and London cities use IBM’s Smart Transportation solutions to adjust buses and traffic flow in real time (Bélissent, 2010). Consulting firms often provide local governments with systems integration services to improve their efficiency. Accenture and Capgemini provide utilities information on smart meter integration for increased efficient. In the field of healthcare, big names such Cisco, GE, IBM, Siemens, InterSystems, McKesson, MTN, and Telefonica are working as vendors to expand telemedicine solutions or enable infrastructure for mobile healthcare services. Other examples include public safety where Cisco’s Video Surveillance Manager offered cities access to cameras and command centers with live and recorded video (Bélissent, 2010). Companies provide services in addition to technology for ease of use for the government. However, using off the shelf solutions could be very costly.

2.2.3 Citizens

Active citizen participation is essential I creating a sense of ownership and commitment to facilitate smoother smart city project integration at the community level. The literature has repeatedly emphasized the significance of citizen participation in input in smart city initiatives from inception to deployment.

Open government initiatives in some smart cities provide access for citizens to obtain information from leadership. The innovative atmosphere in communities can spur “smart” economies (Borsekova, Koróny, Vaňová, & Vitálišová, 2018).

The power of local community and organizations may vary in the establishment of a smart city dependent on the government infrastructure. A local authority may provide greater input to citizens, businesses, and other non-governmental authorities in terms of budget and finance. While a centralized governing body may make complete decisions without requiring such inputs. Without feedback the possibility of building mega smart cities that end as “ghost” cities is very real (Sorace & Hurst, 2016).

2.3 Information Technology Infrastructure

Smart cities function by taking advantage of a distributed network of sensors connected via an Internet of Things (IoT) based architecture. This is often depicted as a complex layer of acquiring data, contextualizing information, deriving knowledge, and applying useful services (Moreno et al., 2017) The information collected by the sensors must be integrated into a common platform due to the diversity of communication protocols. This data is then transferred, filtered, synthesized, and interpreted to produce useable information. These computer algorithms control various services as output. The feedback between the sensors and the service network create a “smart” feedback mechanism with the goal of managing cities efficiently (Moreno et al., 2017).

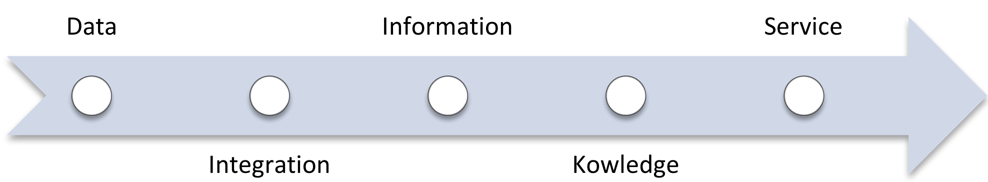

Figure 6 Smart City Information Flow Architecture

2.3.1 Sensors

The foundation of a smart city is the distributed network of internet enabled data collecting devices. These sensors can range from a closed-circuit television (CCTV) camera network, traffic cameras, environmental monitoring devices, or GPS. Sensors can be used to detect motion, speed, direction, presences, and even sounds. For example, acoustics sensors can detect and triangulate gunshots using artificial intelligence (Shweta Srivastava, Aditya Bisth, 2017). Unmanned aerial vehicles (UAV) also known as drones are being used as sensors. Drones can be used for surveillance and cover large swathes of land to monitor crowds or even in surveying fires. Connected power meters can provide real-time energy monitoring. Sensors provide the data that is transmitted to the cloud where the information is stored, processed, and analyzed by computer algorithms. The useful information that can be interpreted from this network provides the actionable intelligence that powers a smart city (Shweta Srivastava, Aditya Bisth, 2017). Currently, the greatest number IoT devices being used in smart cities are in smart homes and commercial buildings (See Figure 7). This is followed by usage in transport, utilities, and public services.

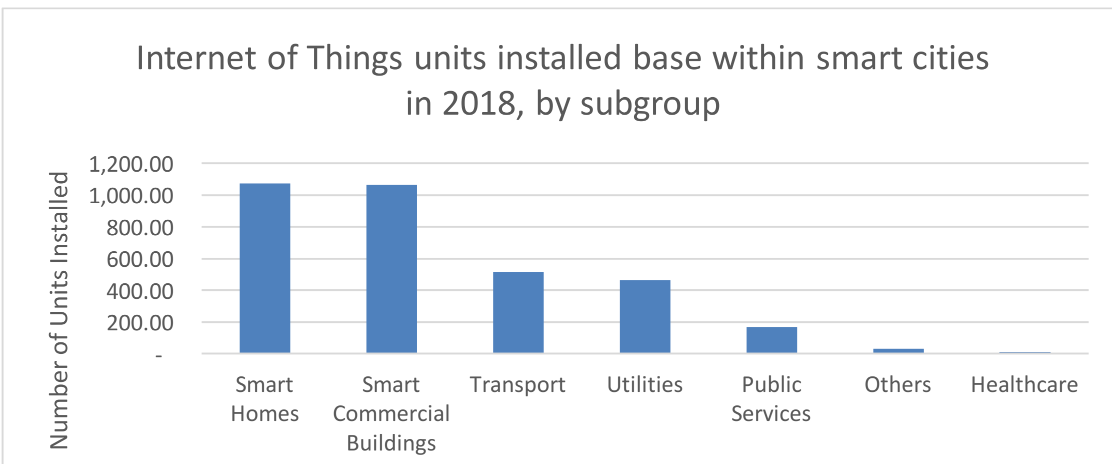

Figure 7 IoT Units Installed in 2018, adopted from CSI Magazine 2018

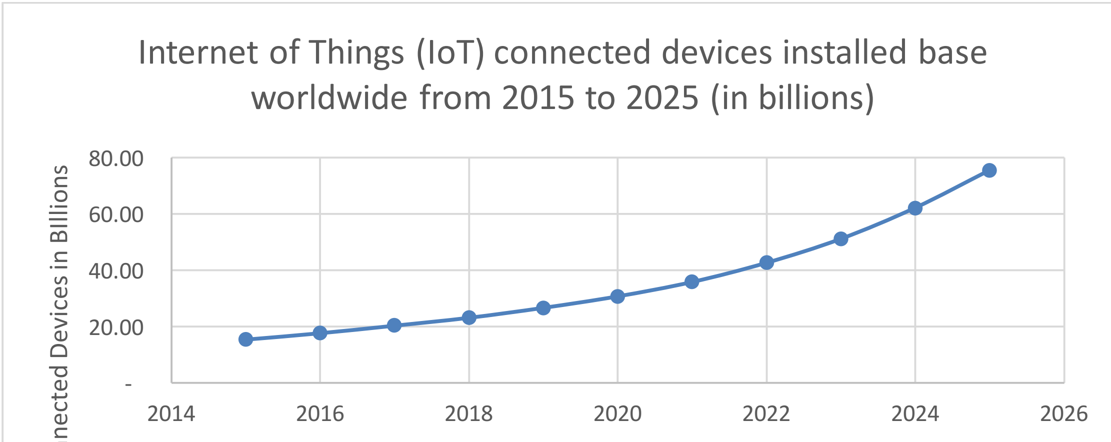

Figure 8 IoT Connected Devices Installed Base Worldwide from 2015 to 2025 (HIS, 2017

The sheer number of connected devices being installed displays an exponential growth and is forecasted to exceed 75 billion by 2025 (See Figure 8). As the number of IoT connected devices exponentially increases over-time worldwide, the amount of data that city planners have access to does as well. Managing this "big data" poses a challenge to technocrats.

2.3.2 Big Data

Smart cities are dependent the information they collect from the distributed sensor networks to generate useful actions. Planners must be able to quickly collect, filter, process and analyze data to create useful information. Smart cities are often noted as taking advantage of “big” data in applications of transportation, healthcare, utilities, and even education.

Figure 9 Typical Big Data Sources from Smart City Components

This is often seen as collecting as much data as possible from as many sources as possible from distributed networks online and in the physical world. Some of the challenges attributed to big data are that the data is often in an unstructured and disorganized form. There are several parameters that can be used to characterize big data. The size or amount of data depends on the amount of sources and creates storage requirements. The rate at which data is generated and processed is sometimes generates processing requirement. In smart cities a variety of sensors and data inputs are present. This also leads to many different types of data and communication structures. Is the data reliable and reproducible? Does the data collected result in useful information? The usefulness of the data may vary, and planners must be able to determine how the big data they have access to falls within these categories.

Table 1 Characteristics of Big Data adopted from Kitchen and McArdle, 2016

Volume	Refers to the enormous quantities of data that has been created from various sources
Velocity	Refers to the speed at which data is generated, stored, analyzed and processed. An emphasis is being put recently on supporting real- time big data analysis
Variety	Refers to the different types of data being generated. Data comes in structured, semi-structured and completely unstructured. The less structure the data has, the harder to extract useful information
Exhaustively	Refers to capturing the data of an entire system rather than a sample
Fine-grained	Refers to the fine-grained in resolution and uniquely indexical in identification
Rationality	Refers to the containment of common fields that enable the conjoining of different datasets
Extensionality	Refers to the ability to add/change new fields easily at scale
Veracity	Refers to the accuracy and truthfulness of the captured data and the meaningfulness of the results generated from the data for certain problems
Value	Refers to the possible advantage big data can offer a business based on good big data collection, management and analysis
Variability	Refers to how the structure and meaning of data constantly changes especially when dealing with data generated from natural language analysis for example

While data is generated from a variety of data sources in a smart city, it is usually collected and processed in a centralized server. This cloud storage and information processing empower planners to easily produce knowledge that can be used to enhance governance, economy, environment, health, transportation, and many other sectors in a city.

Managers have a variety of ways of collecting information from its citizens. This often results in big datasets stored in clouds. The city can only become smart when planners utilize this data to generate useful action from interpreting this information. Data informed decision making empower smart city leaders. They are able to analyze the data to get descriptive, diagnostic, and even predictive information to support their decisions and actions. As we increase the use of machine learning algorithms, analytics may shift from statistical and human centered to automate and computer generated.

Chapter 3

SELECTED EXAMPLES

3.1 Smart Street Lighting

In most cities, street lights are operated temporally, turning on at set time periods. Energy savings can further be increased by using high efficiency lamps or introducing technology such as solar panels. Additionally, some governments regulate light intensity levels depending on road type. For example, in Jakarta, greater illumination is required on busy arteries as compared with pedestrian roads.

Table 2 Illumination Standards for Cities Set by the Indonesian Government, adopted form (Escobar et al., 2014)

Road Classification	**Illumination level (lux)**
Pedestrian	(1-4)
Local road	(2-5)
Collectors	(3-7)
Arterials	(11-20)
Arterials with access to highways	(15-20)

A smart-city implementation takes street lighting efficiency to the next level. Using traffic data and sensors, smart cities can implement adaptive systems that dim lights based on traffic intensity probability and real time sensing (Al Irsyad & Nepal, 2016; Escolar et al., 2014; Marino, Leccese, & Pizzuti, 2017; Nefedov et al., 2014; Virendra, Sathyadeep, Ravi, & Mathan, 2016).

Marino et al. present a smart predictive monitoring and adaptive control system using cameras in the city of L'Aquila, Italy. These Smart Eye cameras include optical sensors and automatic data processing which evaluate weather conditions, traffic/people presence (Marino et al., 2017). They initially collected data for traffic flow and compared with various models generated. The models were evaluated using the mean absolute percentage error (MAPE) formula:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{A_t - F_t}{A_t}\right| * 100 \qquad (3.1)$$

Where N is the number of observations, A is the actual value, and F is the forecasted value.

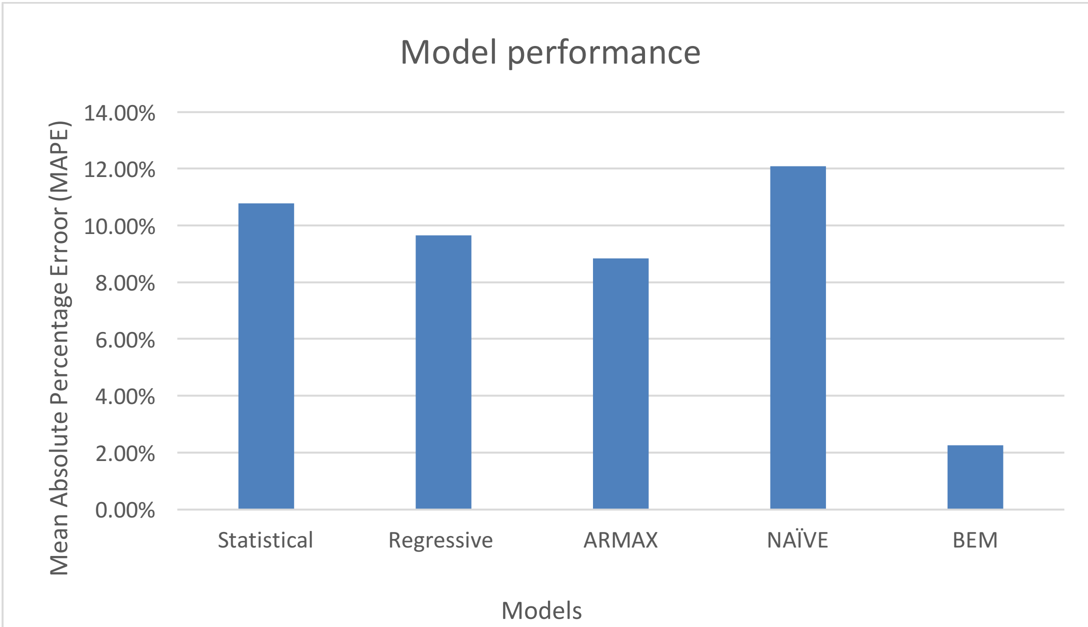

Figure 10 Predicted vs. Actual Traffic Flow Model Performance, adopted from (Marino et al., 2017)

Ultimately the NAIVE model performed the best with a MAPE of 12.08% (See Figure 10). Applying the predictive model, instead of the standard government lighting regulations resulted in a 30% energy savings (Marino et al., 2017). Escolar et al. present an algorithm that controls light intensity state based on time of day (off, low, medium, and high), presence sensors for pedestrians and vehicles, and environmental sensors (Escolar et al., 2014). The model depends on a series of lamp-mounted sensor nodes that send data to cluster head. These clusters then send information to data collectors where it is processed. The cluster heads then send commands controlling lamp intensity. This allows for maximized safety and cost efficiency. For example, on a less busy street lights can be dimmed. However, an overcast daytime scenario would trigger the lamp to turn on which would add cost, but allow for greater visibility and safety. Researchers estimate that 50% cost savings could be achieved on low-usage roads (Nefedov et al., 2014). The resulting savings can be used to further expand lighting areas and increase public safety.

3.2 Smart Transportation (public transport)

Public transportation systems have lower energy consumption per passenger as compared with cars. These systems can result in lower pollution levels and less traffic congestion. However, for greater consumer utilization, the system must be optimized to maximum efficiency. By monitoring transport patterns, more people can be serviced without wasting resources.

The city of Murcia has a population of under 500,000 in 2017, with 28 stations spanning 18 kilometers (Moreno et al., 2017). One method of transport popular in this European city is the tram service. Experts used data collected from smart cards to model tram usage based on the time of day, trip origin, trip destination, and age group of travelers (Moreno et al., 2017). One major assumption of the model which uses a fuzzy clustering algorithm is based on the trip-chaining method (Moreno et al., 2017). As only origins are tracked by the system, the location of the origin is assumed to be the location of last trips destination. Creative methodologies used to extract relevant information where data does not exist is essential to designing systems in smart cities. Data patterns informed planners that daily traffic focused on lines connected specific stations while during the evening the load was spread along the whole system. This information was used to target consumers to increase ride participation.

3.3 Smart Parking

A common cause of congestion in cities is caused by drivers looking for parking spaces. By utilizing smart parking systems, city planners can provide drivers with open parking space information using sensors connected to IoT-infrastructure. In addition to providing information, officials can better design parking areas where greater vehicle density is reported (Arasteh et al., 2016).

As technology advances, an increased number of cars are being launched with a variety of fuel sources. The distribution networks to provide the energy to the cars can be designed using data derived from smart cities. The allocation of plug-in vehicles spaces were modeled for a city in western Australian a city (Neyestani, Damavandi, Shafie-Khah, Contreras, & Catalão, 2015) (Dailami et al., 2015).The algorithm applied first begins by determining behavior and then develops a model based on defined objectives. This results in the generation of the optimal location for charging stations within the city.

3.4 Smart Building

In cities, buildings are one of the most relevant drains on energy resources. To manage energy usage, smart design can be used to automate devices throughout the building resulting in a more comfortable indoor environment and efficient energy usage. One project in the European city of Murcia uses infrared (IR) transceivers, environmental sensors, a weather station, presence sensors, energy usage meters, and weather forecasts to monitor room temperature, humidity, light levels both indoor and outdoor (Moreno et al., 2017). This data is then cleaned, processed, and interpreted using regression models to control the HVAC system. The building management system provides localized control at a room level based on a balance of comfort and minimization of energy usage.

3.5 Smart Public Safety

Smart cities can take advantage of the distributed network of sensors to detect and even prevent crime. Cameras using face detection software can automatically search for suspects. Crime data can be analyzed by location to detect hotspots of crime and increase police presence. Gunshot detection sensors can quickly alert police and reduce casualties from gun violence. The intersection of surveillance, sensors, analytics, and people create a cyber-police force aimed at making cities smarter and safer. Police forces are taking advantage of technology and being equipped with software that automatically detects crime autonomously using artificial intelligence for example the AISight software (Shweta Srivastava, Aditya Bisth, 2017).

In San Francisco, the police department deployed the Shotspotter gunfire detection system and reduced homicide to an all-time low (Shweta Srivastava, Aditya Bisth, 2017). The system utilizes an artificial neural network that applies a temporal pattern recognition algorithm that can identify a gunshot. The time, location, and distance between events are reported to police in the ShotSpotter platform.

3.6 Smart Tourism

Tourism is an important factor in the budgets of many cities. To better service guests of the city, planners use sensor data to provide personalized recommendations to visitors. In the smart city of Trento, Italy, planners use a software program called TreSight that utilize sensors, open-data, and user participation to provide tourism recommendations (Sun, Song, Jara, & Bie, 2016). The system is based on sensors within bracelets that provide crowd size information, interact with cell phone, and track location. Additional information is provided by environmental sensors including temperature, humidity, and noise (Sun et al., 2016). This sensor data is uploaded to a centralized database where the processing considers weather, current events, safety and generates personalized recommendations.

3.7 Smart Energy / Smart Grid

In cities worldwide, the demand for energy can stress the capabilities of the power infrastructure. Smart grid systems have the ability to manage energy demands in a more efficient way. Maintaining the network infrastructure can also be aided by monitoring, diagnosing, and automating techniques (Jaradat, Jarrah, Bousselham, Jararweh, & Al- Ayyoub, 2015). In addition to optimization and maintenance, many cities are also attempting to increase the share of renewable energy in their energy portfolio. One challenge these utilities may face by using some low carbon energy sources including wind and solar is their inherent variability (Lu et al., 2016). But by utilizing smart features, the grid can better integrate renewable energy sources because of added flexibility.

Chapter 4

DATA ANALYSIS

4.1 Data Sources and methodology

Smart city projects aim to manage resources optimally. One result of increased efficiency should be reduced energy usage and reduced greenhouse gas emissions. To test this hypothesis, we will compare carbon dioxide (CO_2) emissions per capita in specific cities that were ranked by a smart score (Easy Park Group, 2017; Hoornweg, Sugar, & Lorena Trejos Gómez, 2011; The World Bank, 2010).

Table 3 Factors Used to Derive Smart City Rankings adopted from (Easy Park Group, 2017)

Transport and Mobility	Sustainability	Governance	Innovation Economy	Digitalization	Living Standard	Expert Perception
Smart parking	Clean energy	Citizen Participation	4G LTE	Living standards	Business ecosystems	How the city is becoming smart
Car Sharing Services	Smart Building	Urban planning	Internet speed			
Traffic	Waste disposal	Education	Wifi hotspots			
Public Transport	Environmental protection	Digitalization of government	Smartphone Penetration			

The factors used to derive the smart city rankings were Smart Parking, Car-Share, Traffic, Public Transport, Clean Energy, Smart Building, Waste Disposal, Environment

Protection, Citizen Participation, Digitization of Government, Urban Planning, Education, Business Ecosystem, Living Standard, Internet Speed,4G LTE, WIFI Hotspots, Smartphone Penetration, and Expert Perception (Easy Park Group, 2017). These factors were then grouped into categories of Transport and Mobility, Sustainability, Governance, Innovative Economy, Digitalization, Living Standard, and Expert Perception (Easy Park Group, 2017) . A standard score was calculated based on equation 4.1.

$$Score_i = 1 + 9\left(\frac{X_i - X_{min}}{X_{max} - X_{min}}\right) \qquad (4.1)$$

$$\begin{aligned} Final\ Score_i = {} & 25\%\ Transport\ and\ Mobility_i + 12.\%\ Sustainability_i \\ & + 17.5\%\ Governance_i + 2.5\%\ Innovation\ Economy_i \\ & + 17.5\%\ Digitalization_i + 10\%\ Living\ Standard_i \\ & + 15\%\ Expert\ Perception_i \end{aligned}$$

Hoornweg et al. and World Bank total CO_2 emissions per capita in specified years for specific cities (See Table 5). The CO_2 emissions were used to represent greenhouse gas emission (GHGe) in this analysis. Analysis and visualization were performed in R Studio.

Table 4 City Per Capita Greenhouse Gas Emissions, adopted from Hoornweg et al., and World Bank 2011

City	GHG Emissions (tCO2e/capita)	City	GHG Emissions (tCO2e/capita)
Buenos Aires	3.83	Oslo	3.5
Sydney	20.3	Porto	7.3
Dhaka	0.63	Seoul	4.1
Brussels	7.5	Singapore	7.86
Rio de Janeiro	2.1	Ljubljana	9.5
Sao Paulo	1.4	Cape Town	7.6
Calgary	17.7	Barcelona	9.86
Toronto	11.6	Madrid	6.9
Beijing	10.1	Stockholm	3.6
Shanghai	11.7	Geneva	7.8
Tianjin	11.1	Rotterdam	29.8
Prague	9.4	Bangkok	10.7
Helsinki	7	London	9.6
Paris	5.2	Glasgow	8.8
Frankfort	13.7	Austin	15.57
Hamburg	9.7	Denver	21.5
Stuttgart	16	Los Angeles	13
Athens	10.4	Minneapolis	18.34
Bologna	11.1	New York City	10.5
Naples	4	Portland, OR	12.41
Turin	9.7	Seattle	13.68
Veneto	10	Washington D.C	19.7
Tokyo	4.89	San Francisco	10.1
Amman	3.25	San Diego	11.4
Mexico City	4.25	Miami	11.9
Kathmandu	0.12	Philadelphia	11.1

4.2 Results and Analysis

The CO_2 emission data and the smart city factor rankings were compiled into a central database. This set was then filtered to remove any missing information reducing the number of cities from 100 to 35. The R-scripts used for conducting the analysis can found in the appendix.

4.2.1 Regression Modeling

To measure the relationship between the smart city rank and GHGe, a linear regression model was fit. This technique is widely used for predicting a quantitative response of Y on the basis of predictor variable X. In its simplest linear form, it's written as

$$Y \approx \beta_0 + \beta_1 X \tag{4.2}$$

Where β_0 and β_1 are two unknown constants that represent the intercept and slope terms for the linear model. They are known as the model coefficients or parameters. In the presence of more than one explanatory variable, the processes is termed multiple linear regression which is formulated as the following

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \in, \tag{4.3}$$

The model allows us to examine and explain the variation in the response variable that can be attributed to the variation in the explanatory variable. Likewise, linear regression models allow us to quantify the strength of the relationship between the response and explanatory variables. (Casella, Fienberg, & Olkin, n.d.)

There appeared to be no significant correlation generally between smart city rank and GHG emissions (r^2=0.02, p-value=0.20). Grouping the cities by region and then applying the regression generated a significant negative correlation with significance level of less than 0.1, adjusted r-squared value of 0.53 and p-value <7.8E-5. For the South American cities, a stronger negative correlation was observed (p-value <0.05) (See Figure 27). It seems that generally, the "smarter" the city in a region, the less GHG emissions are generated. South American smart cities most clearly display this. The scatterplot of this data shows that all regions exhibit a similar negative tendency (See Figure 11).

Table 5 Linear Regression Model for GHGe vs Smart City Ranking. Adjusted R-Squared value of 0.5325 and P-value of 7.75E-5

	Coefficient	**Standard Error**	**t-statistic**	**p-value**
(intercept)	15.51310	3.6379	4.264	0.0002060
EP Rank Score	-1.02440	0.5173	-1.98	1.0575740
Asia	-1.43610	3.5646	-0.403	0.6901000
Europe	-1.75340	3.3903	-1.517	0.6090870
North America	3.29700	3.6324	0.908	0.3717960
Oceana	12.39800	4.706	2.625	0.0135730
South America	-8.71520	3.415	-2.552	0.0164510

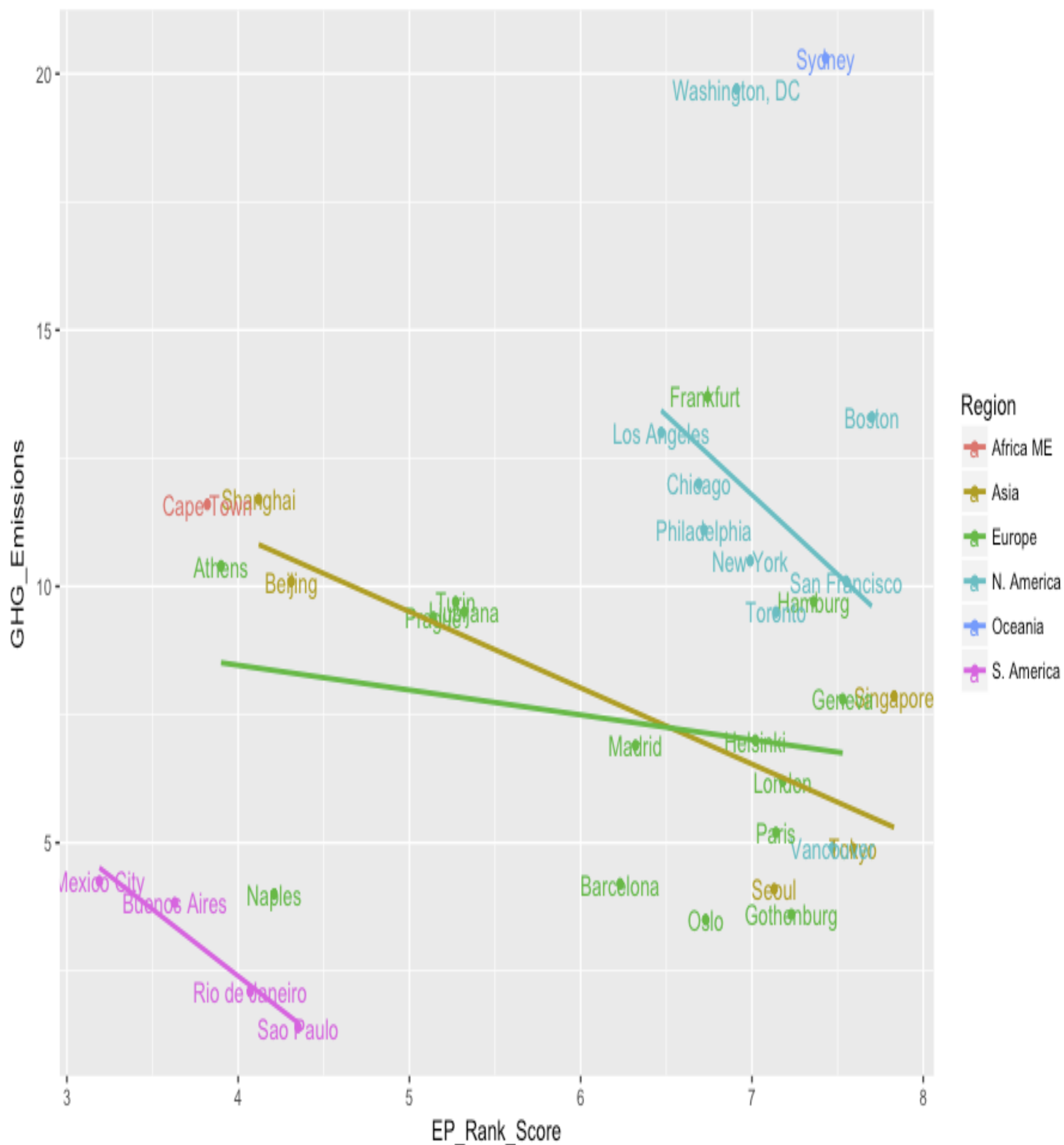

Figure 11 Greenhouse Gas Emissions vs. Smart City Ranking grouped by region Africa & the Middle East, Asia, Europe, North America, Oceania, and South America. Generally, within a region, the smarter a city, the less GHG emissions per capita.

4.2.2 Correlation Analysis

The smart factors relating to transportation and mobility include smart parking features, car share programs, traffic congestion levels, public transport satisfaction. A positive correlation was found between smart parking and car sharing services and GHG emissions seen in Figure 12. This is not surprising as more cars whether individually owned or shared would produce greater emissions.

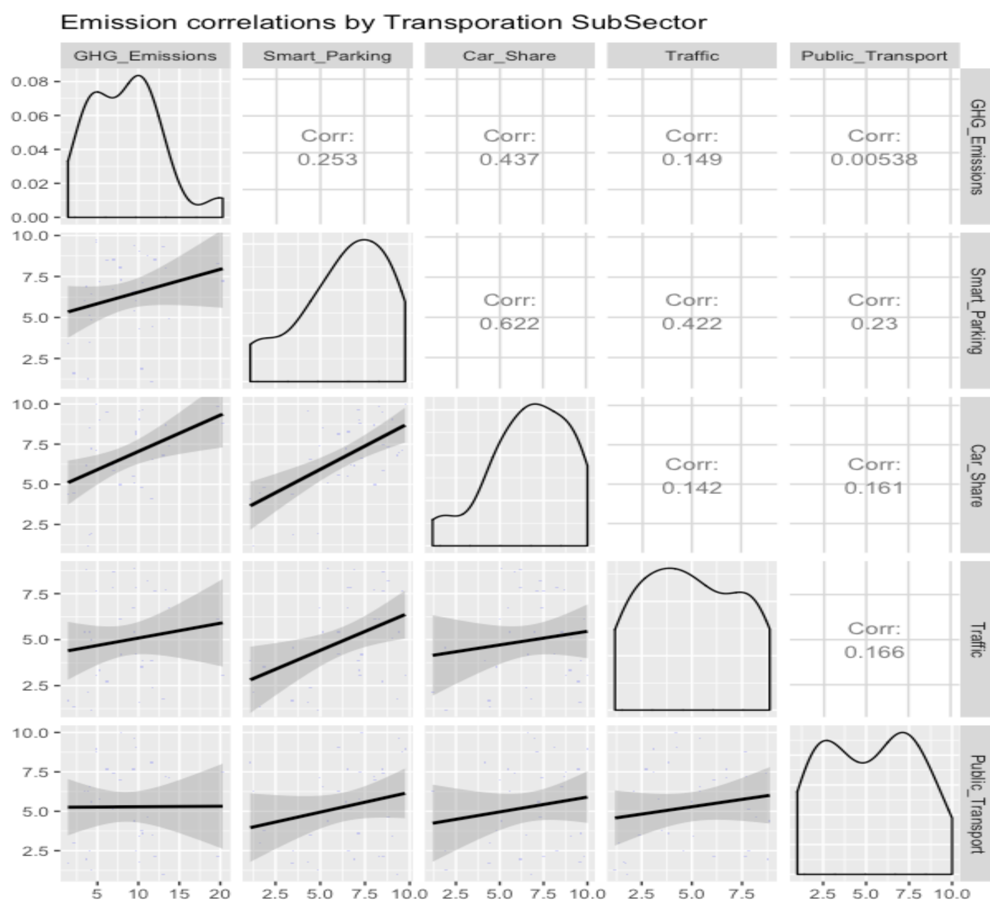

Figure 12 Correlation between greenhouse gas emission and transportation factors

The factors representing a sustainably smart city include use of clean renewable energy, energy efficient building investments, waste disposal in landfills, and environmental protection. There is a clear negative correlation between clean energy and environmental protection and decreased emissions in these smart cities (See Figure 13).

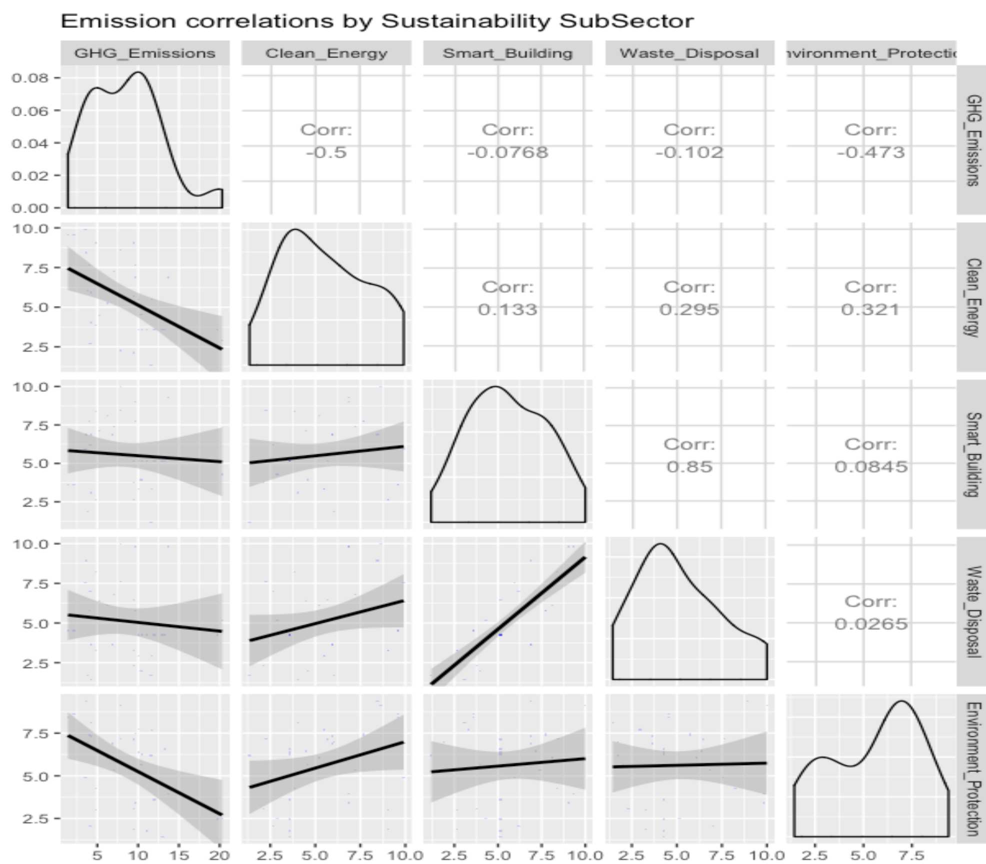

Figure 13 Correlation Between Greenhouse Gas Emission and Sustainability Factors.

There appears to be a positive correlation between education levels (0.432) and business activity (0.379) with greenhouse gas emissions. Greater business development in a city could produce greater activity and result in higher emissions.

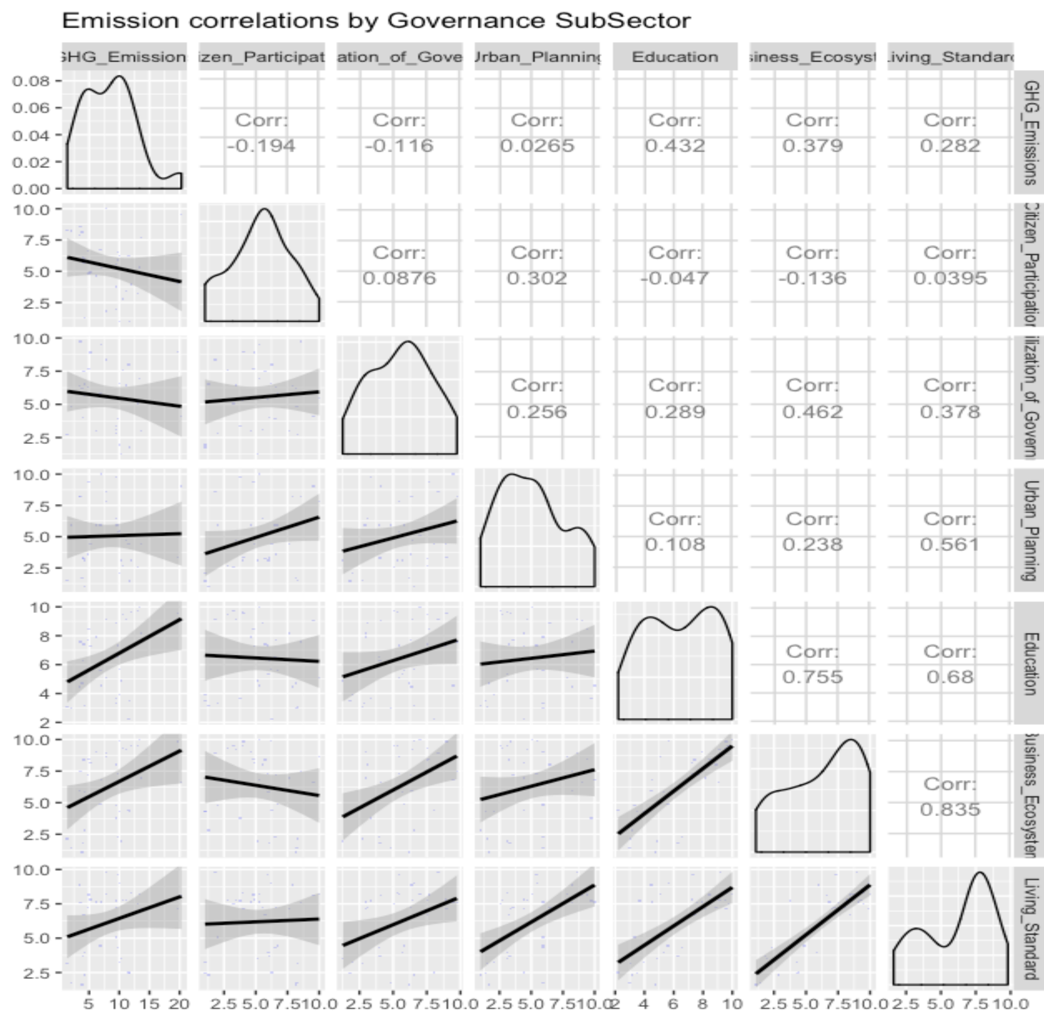

Figure 14 Correlation Between Greenhouse Gas Emission and Governance Factors

No strong correlations between network speed and technology penetration were found with GHGe (See Figure 15).

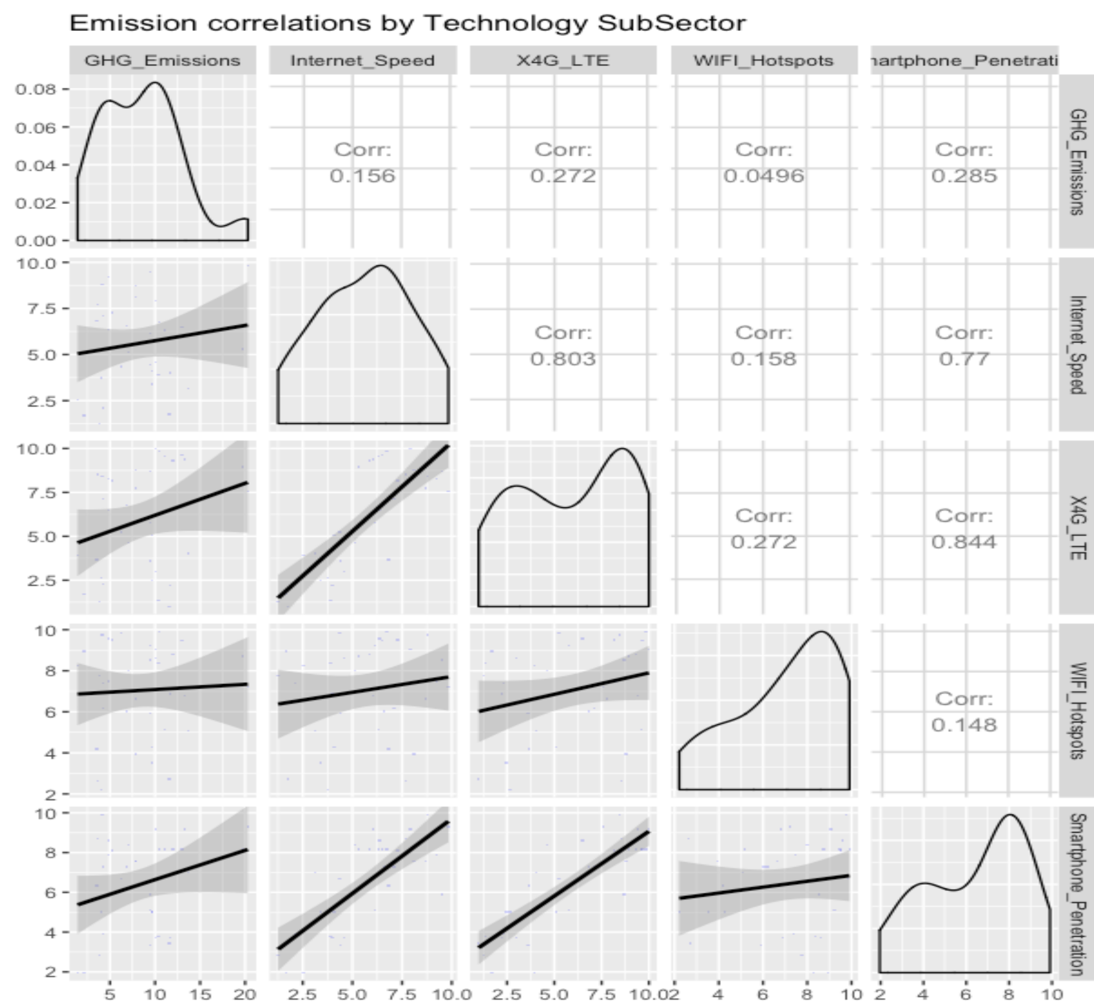

Figure 15 Correlation Between Greenhouse Gas Emission and Technology Factors

4.2.3 K-means Cluster Analysis

Rather than group smart cities by region, performing cluster analysis allows for a more natural grouping by characteristics (See Figure 16). This method, clustering, can be used as a viable method to gain insight into the distribution of data. This technique is a type of unsupervised learning that allows groups with similar observations to be grouped together. It's used to uncover hidden structures of the data and to simplify the data into small summaries. At its core, this clustering seeks minimize the intra-cluster distance and maximize the inter-cluster distances. Several distance measure methods can be used such as The Euclidean distance, Manhattan distance, Minkowski distance, Mahalanobis distance, Maximum distance and Euclidean distance. Unlike other unsupervised learning techniques such as Principal Component Analysis, clustering seeks to find homogeneous subgroups among the observations in the data. Different methods for clustering exist but the two most popular are K-means clustering and hierarchical clustering. (Martey, Ahmed, & Attoh-Okine, 2018). For this analysis, K-means clustering was used. To perform the analysis four clusters were specified based city region. The K-means algorithm then assigned each observation into one distinct cluster and is expressed as follows (Casella et al., 2017)

$$\frac{mnimize}{C_{1,\ldots\ldots}C_K} = \left\{\sum_{k=1}^{K} W(C_k)\right\} \qquad (4.4)$$

Where for cluster C_k is a measure $\mathrm{W(C_k)}$ of the amount by which the observations within a cluster differ from each other. To define within cluster variations, squared Euclidean distance is used, which is defined as the following.

$$W(C_k) = \frac{1}{|C_k|} \sum_{i,i^1 \epsilon C_k} \sum_{j=1}^{p} (x_{ij} - x_{i'j})^\wedge 2 \qquad (4.5)$$

Where C_k denotes the number of observations in the *k*th cluster. In other words, the within-cluster variation for the *k*th cluster is the sum of all of the pairwise squared Euclidean distances between the observations in the *k*th cluster, divided by the total number of observations in the *k*th cluster. Combining equations (1) and (2) gives the optimization problems that defines K-means clustering, (Casella et al., 2017).

$$\frac{mnimize}{C_{1,\dots\dots}C_K} = \left\{ \sum_{k=1}^{K} \frac{1}{|C_k|} \sum_{i,i^1 \epsilon C_k} \sum_{j=1}^{p} (x_{ij} - x_{i'j})^\wedge 2 \right\} \qquad (4.6)$$

To optimize equation (3), the K-means algorithm randomly assigns a umber from 1 to K, to each of the observations. An iterative process follows until the cluster assignments stop changing. For each of the K clusters, the cluster centroid is computed. The *k*th cluster centroid is the vector of the *p* feature means for the observations in the *k*th cluster. Finally, each observation is assigned to the cluster whose centroid is closes, where the closest is defined as the nearest Euclidean distance. (Casella et al., 2017).

Even with clusters extracted regional aggregation remains apparent. The linear regression model taking cluster group into account show negative correlation between GHGe and smart city ranking (See Figure 16). There are cities that are smart and low emitters, mostly located in Europe (cluster 2). There are cities that are very “smart”, but per capita emit more greenhouse gases, mostly located in the United States (cluster 4). There are cities that are less smart and either emit more including Chinese cities (cluster 3) or less including many South American cities (cluster 1).

Table 6 Linear Regression Model of Greenhouse Gas Emissions vs. Smart City Ranking Grouped into Clusters

	Coefficient	**Standard Error**	**t-statistic**	**p-value**
(intercept)	11.75130	6.4628	1.818	0.0790200
EP Rank Score	-0.57730	0.961	-0.601	0.5525100
Cluster 2	-1.46970	1.6988	-0.865	0.3938100
Cluster 3	6.07310	1.7647	3.441	0.0017200
Cluster 4	-2.86990	3.0467	-0.942	0.3537300

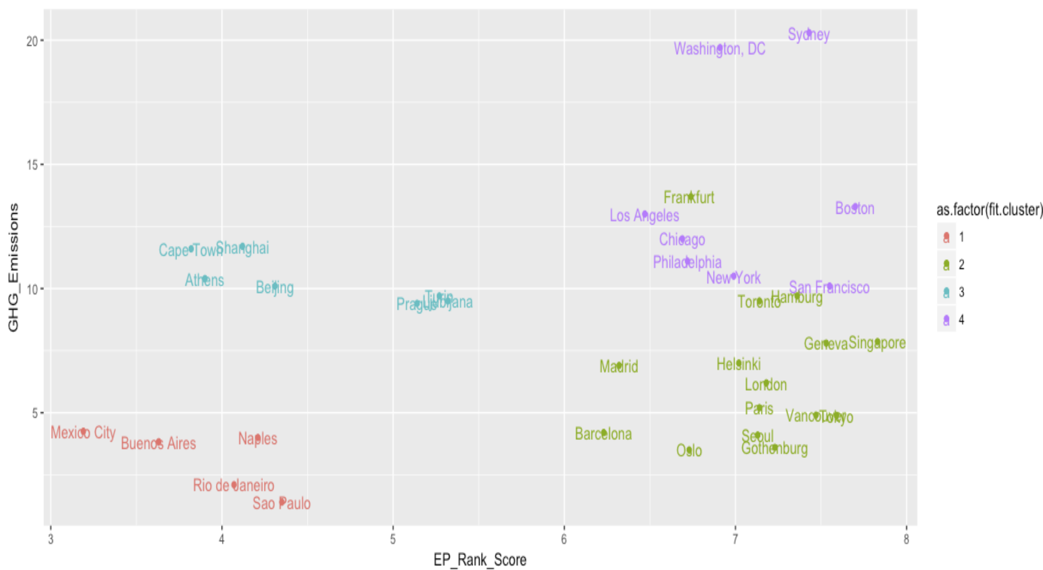

Figure 16 Greenhouse Gas Emissions vs. Smart City Rankings with Cluster Analysis

No strong correlations were observed between the expert ranking or summary ranking of smart cities and greenhouse gas emissions except when region or cluster were considered. Because the definition of smart cities is not standardized, these two ranking are subjective values. The basis of both depend on decisions made. The experts polled decided to rank the cities based on their observations and experiences. The researchers decided the weighting formula to calculate the summary ranking value.

The smart city factors with the greatest correlation with greenhouse gas emissions related to transportation, energy, and economic productivity. If city planners want to optimize emission reductions, they should more strongly focus their smart technologies in those three areas.

Chapter 5

CONCLUSION, CHALLENGES AND CONCERNS

5.1 Concluding Remarks

This thesis explored the idea of smart city initiatives as a means for sustainable urban development. While there is still much confusion about a singular universal definition of a smart city is and at its essence amorphous, a few key features are present. Smart cities focus on optimizing resource usage using data, algorithms, and connected technologies while serving the ever-growing populations of urban areas. The stakeholders (policy makers, bureaucrats, business, and community members) benefit from dynamic interaction of systems and prediction based on models. This includes sectors of energy, infrastructure, transport, technology, governance, education, health, and security. These projects all utilize data collecting networks of internet enabled devices to manage resources in a sustainable and efficient way for the optimization of economic resources and social benefit. Because smart city objectives are highly regional, even local, different cities may require different technological solutions. These differences make it difficult to a set a specific definition of what "smart" city is. Rather than defining what a smart city is, it may be more useful to define what a smart city does. The author proposes the defining of a "smart" city process incorporating a sensing layer, a transmission layer, a processing layer, and an application layer (See Figure 36). This flexible definition can be applied to smart city projects at both small and large scales. The sensing layer contains all the connected sensing devices. The transmission layer describes the transmitting and receiving of data between connected devices to central computing. In the process layer is where data is stored and processed with algorithms applied. The actuation layer is defined by the useful applications and services actuated in the real-world.

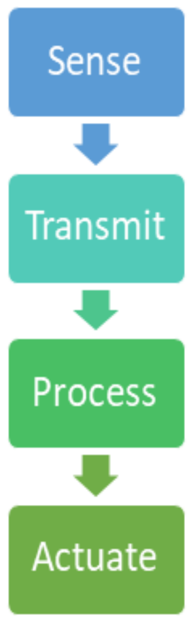

Figure 17 Working Smart City Framework

The analysis portion of this work has demonstrated that the “smartness” of a city does not necessarily translate into sustainable development outcomes. North American cities for example, though relatively smart have shown to have relatively high unsustainable emissions levels. European cities on the other hand, have shown to leverage “smartness” in reducing city emission levels. This is means that sustainable development is a multifaceted problem that is not fixed with ‘smartness” in a particular aspect of city structure alone. As city planners continue to face challenges managing increasing urban populations, a holistic approach for sustainable urban development will be vital. In the meantime, because smart city initiatives are local, this research has highlighted specific factors city stakeholders can focus on to achieve tangible results in particular areas.

5.2 Challenges and Concerns

One common challenge facing smart cities is the large array of communication protocols of the sensors in-use. Integration of sensors with varied, proprietary, or even outdated communication protocols can cause problems. Planners must take into account methods to synthesize different protocols and focus on future-proofed open source solutions (Ahlgren, Hidell, & Ngai, 2016; Moreno et al., 2017). Today, many of the IoT connected sensors utilize proprietary protocols. Other companies such as Google, Apple, Cisco, Ericsson, and Qualcomm try to advance proprietary protocols and communication standards (Valerio, 2016). Adoption of standard and open protocols commonly used will result a more robust smart city IoT network as city planners will not be limited by a specific companies’ equipment.

The aim of smart cities is to best serve the population; however, people exhibit dynamic behavior. Providing customized and efficient services will require an increasing number of smart objects that are able to process and interpret complex information on a local level (Moreno et al., 2017)

In western countries, smart city projects often begin as pilot projects sponsored by tech companies. Some companies of note include Cisco, Google, Apple, Microsoft, Schneider-Electric, and IBM who want to increase market-share of their connected devices (Valerio, 2016). Cities are presented with pilot programs, but cannot upscale them as the cost was not feasible with their budgets. To avoid these problems, city planners must clearly define their needs before starting a pilot so that the solution can improve the lives of citizens.

Being surrounded by sensors create a concern for citizens' privacy. Smart city infrastructures must continue to secure data collected as it passes information to third parties and various applications (Moreno et al., 2017). Because Smart cities are characterized by ubiquitous nature of sensors which may cause concern in terms of privacy and cybersecurity.

Smart cities are often heralded as utopian innovations and the solution for global problems. While these initiatives aim to solve real problems, their implementation pose specific challenges. The city planners must design flexible systems that can grow in the future within budget constraints. The benefits of the system (cost, waste, energy, crime reduction) must outweigh the costs. As with any technology, the system must be protected from hackers and have built in redundancies to avoid system failures.

Investments in fast and reliable networks, storage and processing, and the talent that can run these are necessary expenditures for a successful smart city.

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