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Smart Cities and Communities: A Key Performance Indicators Framework

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Smart Cities and Communities: A Key Performance Indicators Framework

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Abstract

This publication presents research findings and scientific work that advance the development and progression of smart city and community measurement methodology. The term 'smart,' as used in the phrase 'smart cities,' is defined here as the efficient use of digital technologies to provide prioritized services and benefits to meet community goals. Without reliable measurement methods for 'smart,' there is a gap in the ability to answer questions such as 'how smart is my smart city plan,' or 'how can my community strategy be made smarter?' This report addresses this gap by introducing a measurement framework for assessing the direct and indirect benefits of smart city technologies.

The Holistic KPI (H-KPI) Framework builds on conventional Key Performance Indicators (KPI) methods and accounts for unique characteristics such as varying districts and neighborhoods, differences in population and economic scale, the reuse of previously deployed technologies, and other factors relevant to a city or community. The Framework provides the basis for developing measuring methods and tools that allow for integration, adaptability, and extensibility at three interacting levels of analysis – i.e. technologies, infrastructure services, and community benefits.

The H-KPI method provides a structured representation of smart city/community information flows that supports system visualization, serves as the basis for quantitative metrics for measuring 'smart,' and enables computational methods for systems design, analysis, operations, and assurance. The five core metrics of the method are: alignment of KPIs with community priorities across districts and neighborhoods; investment alignment with community priorities; investment efficiency; information flow density; and quality of infrastructure services and community benefits. Applications of the H-KPI approach include strategic planning, systems design and assurance, and operations management.

Keywords

Cyber-physical systems (CPS); Data; Data modeling; Holistic key performance indicators (H-KPIs); Internet of Things (IoT); Key performance indicators (KPIs); Smart cities and communities; Smart infrastructure.

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Audience

This document is intended to support city managers, city and community officials, individuals involved in city planning and community development, technology innovators, and others who would benefit from awareness of new Key Performance Indicators (KPI) methodologies; their creation, identification, and assessment based on data generated by smart city systems; and their complex relationships with other data sources, including direct and indirect measurements from emerging technologies in a city or community. Material in the appendices is intended for subject matter technical experts and researchers interested in the details of the methodology.

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Executive Summary

Cities and communities worldwide are increasingly turning to advanced technologies to meet their strategic economic, environmental, safety, and other goals, with the overall goal of improving the quality of life for their occupants. This document presents research findings and scientific work that advance the development and progression of smart city and community measurement methodology.

The term ‘smart,’ as used in the phrase ‘smart cities,’ is defined here as the efficient use of digital technologies to provide prioritized services and benefits to meet community goals, such as economic vitality, equity, resilience, sustainability, or quality of life. Without reliable measurement methods for ‘smart,’ there is a gap in the ability to answer questions such as ‘how smart is my smart city plan,’ or ‘how can my community strategy be made smarter?’ The purpose of this report is to address this gap.

The use of Key Performance Indicators (KPIs) in cities and communities is a common practice, with well-known generic indicators for evaluating and measuring today’s smart city ecosystems. However, many conventional KPI approaches are limited by the following.

- A focus on technology-linked or sector/domain-specific outputs limits measurement of broader indirect benefits essential to accurate assessment of impact and return on investment.
- The lack of a reliable means for measuring real return on investment limits the development of mature smart city business models.
- The application of generic KPI objectives without accounting for unique community characteristics limits the ability to benefit from others’ experiences and adapt solutions from other settings.
- Confining implementation to technology or infrastructure silos without assessing interoperability and scalability limits the ability to evaluate efficient multi-sector, multi-purpose technologies.
- Lack of a reliable means for accounting for local conditions limits realistic evaluation of the technology readiness or maturity level of a city or community in comparison to others.

The Holistic KPI (H-KPI) Framework builds on conventional KPI methods for a more holistic approach with integrated KPIs that facilitate self-assessment, strategic planning, and implementation. The Framework provides a measurement means that accounts for unique characteristics such as the differing needs and capabilities of varying districts and neighborhoods; the need to normalize for variations in population and economic scale; and the reuse of previously deployed technologies, including available data sources and types, platforms for data acquisition and distribution, and installed sensors and actuators.

The primary objectives in developing the H-KPI methodology are to provide for:

1. integration, allowing measurements across sectors, infrastructures, priority areas, and other dimensions characteristic of a given city or community;
2. adaptability, enabling reliable self-assessments in comparisons to other cities and communities while considering their distinctive characteristics; and
3. extensibility, supporting the reuse and repurposing of infrastructures, services, and datasets, along with the integration of new technologies to keep pace with the rapidly evolving digital innovation landscape.

A novel element of the H-KPI method is the assessment of data at three interacting levels of analysis – technologies, infrastructure services, and community benefits. The technologies layer includes sensors and actuators, networks, data systems, and computational hardware and software systems. The infrastructure services layer includes the communications, transportation, energy, water, and buildings sectors, and related services including emergency response, law enforcement, waste management, education, and

city/community services. The community benefits layer includes applications that benefit people and businesses and provide equitable access, including for personal safety and security, business and jobs growth, health care, environmental quality, and other quality of life factors including arts and entertainment.

Robust information flow within and across the three levels of analysis is a key characteristic of a smart city or community and a core element of the H-KPI method. The method provides a structured representation, termed a holistic relationship, of each information flow between a source and a destination over a defined path. Two types of holistic relationships are recognized: dependencies, in which there is single use of a data type (e.g. .xml, .json), and connectors, in which there is reuse of data across multiple applications or services. This approach allows any service or benefit to be described by ordered composition of the dependencies and connectors providing the required information flows. Structured decomposition enables tracing of information flows from high level benefits all the way to original data sources (such as sensor sets), and vice versa. Tracing provides a means for analyzing complex failure or fault modes and for identifying interdependencies that may be affected by updates or other changes to individual information flows. Most importantly, the approach provides for system visualization, serves as the basis for quantitative metrics for measuring 'smart,' and enables computational methods for systems design, analysis, operations, and assurance.

An H-KPI analysis begins with five information collection steps: (1) Data source selection; (2) Data collection; (3) Data modeling; (4) Data cataloging and linking to community priorities; and (5) H-KPI quantification. This fifth step – H-KPI quantification – is the application of a measurement methodology at multiple levels in a smart city or community landscape, including the neighborhoods or districts that make up a community, departments within city government, economic sectors across a city, communities across a region, etc. This approach facilitates smart city planning and management that meets different needs for different districts or sectors, provides equitable access to services and benefits, identifies gaps and opportunities in current implementations, and optimizes smart city/community investments.

The H-KPI measurement method focuses on five metrics:

1. alignment of district and neighborhood KPIs with community-wide priorities;
2. investment alignment with community priorities;
3. investment efficiency;
4. information flow density; and
5. quality of infrastructure services and community benefits.

Additional metrics can be added as needed using the same underlying methodology. Additionally, the method lends itself to more complex assessments of interactions across metrics using methods from statistics, group theory, and array or matrix operations as described in the appendices.

Applications of the H-KPI approach include strategic planning, systems design and assurance, and operations management. For strategic planning, this includes baseline assessment, comparative evaluation of technology options, systems design, and project sequencing. For operations management, this includes comprehensive systems visualization, computational/automated operations management, update and technology refresh management, fault tracing, emergency response, and community systems resilience.

Collectively, this work is intended to enhance the ability of cities and communities to use advanced technologies efficiently and effectively in improving the quality of life for their inhabitants.

1. Introduction

The continuous evolution and extended use of networked technologies is enabling smart solutions in every aspect of our lives, from how individuals live at home, work at the office, access information, and socialize, to how they interact with our environment and surroundings. The use of smart technologies is defining new forms of work and innovation that are making possible the rapid development of new infrastructural services and improvements in the quality of life.

Smart cities represent a significant advancement in the planning and development vision of modern societies. Cities use this vision in their efforts to deal with pressing challenges, including demographic change, urbanization, climate change, public safety, and globalization. Next-generation technologies — notably Internet of Things (IoT) [1][2], Big Data, and artificial intelligence (AI) and machine learning (ML) — are among the main vehicles for realizing this vision.

While the term "smart cities" has often been used for urban environments, this trend has expanded to include suburban, exurban, and rural areas and reflects the deployment and use of technology for service provisioning that addresses the needs of inhabitants, i.e., more *human-centric services*. While smart technologies like IoT, Big Data, and AI continue to be drivers for the evolution of services and usually act as a reference or metric for evaluating smart city technologies performance [3][4][5][6], assessing smart city maturity levels requires a more effective and comprehensive process, including the use of indirect metrics such as perceived quality of service.

1.1. Purpose of the Report

The term 'smart' as applied to infrastructures (e.g., smart grid, smart manufacturing) generally refers to the use of networked information processing systems to enhance user interactions, automation, capability, efficiency, or other functional attributes.

The term 'smart,' as used in the phrase 'smart cities,' is defined here as the efficient use of digital technologies to provide prioritized services and benefits to meet community goals, such as economic vitality, equity, resilience, sustainability, or quality of life. In addition to conventional measures of input, output, and outcomes, this definition includes two additional measurement dimensions: efficiency in the use of digital technologies and alignment with community goals and priorities. The sections that follow describe methods for quantitating these efficiency and alignment dimensions.

Without reliable measurement methods for 'smart,' there is a gap in the ability to answer questions such as 'how smart is my smart city plan,' or 'how can my smart community strategy be made smarter?' The purpose of this report is to address this gap.

Previous measurement methods have focused on inputs (e.g., amount of investment), outputs (e.g., number of sensors), or outcomes (e.g., energy savings) [7][8][9]. While valid, these methods are incomplete and limited in certain respects. First, they are often primarily retrospective and, thus, not well suited to project planning. Second, they typically do not lend themselves to strategic optimization. That is, they do not provide a means for choosing among different technical architectures or for tailoring options to the priorities, needs, and constraints of a particular city or community. Finally, they often do not provide a means for leveraging previous investments and existing infrastructures. The approach described here extends these previous methods to provide a quantitative measurement framework supporting strategic, tailored, and leveraged smart city and community planning and management. While this report focuses on smart cities, the approach is applicable to any smart infrastructure sector.

1.2. Structure of the Report

The report is organized into the following general sections:

1. Introduction
2. Strategic Smart City Goals
3. Overview of Conventional Smart city KPI Approaches
4. Elements of an Effective KPI Methodology
5. Objectives and Approach
6. Components of the H-KPI Method
7. H-KPI Framework: Measuring 'Smart' in 'Smart Cities and Communities'
8. Applying the H-KPI Method

2. Strategic Smart City Goals

Reliable and comprehensive measurement methods are essential for effective planning, implementation, and assessment efforts that can lead to achieving strategic goals in any smart infrastructure project. Smart city initiatives focus on the adoption of technologies and digital services to improve quality of life, provide economic benefits, and promote growth. A smart city today should not be defined just by the number of technologies and new infrastructures or services deployed, but by the benefits that accrue across the city or community. Examples include the following.

Enhanced Service Delivery – The current services in the city can be improved according to real citizen-identified needs in areas such as traffic management, parking, waste removal, road repairs, and street lighting.

Reduced Operating Costs – Emerging technologies like IoT, Big Data, and artificial intelligence (AI) enable the inclusion of new techniques and methodologies to simplify and facilitate operations and to reduce costs by automating resource-intensive processes.

Increased Commerce and Economic Growth – Better services, increased information access, and enhanced network connectivity provide opportunities for business innovation and jobs growth.

Improved Environmental Sustainability – Smart city technologies that improve water and waste management, reduce energy usage and emissions, and enhance environmental monitoring and awareness allow cities and communities to be more environmentally sustainable.

Equitable Access to Services and Infrastructures – All of the inhabitants in a city should have access to the services they need to enjoy a good quality of life. For example, becoming a smart city can be a great motivator to start or expand much-needed internet access to a community. In a smart city, all sectors should be able to create and deploy new services and infrastructures and thus respond to the needs for equitable access, even though this can be expected to be different from city to city and from area to area within a city.

Quality of Life – Regardless of geographic location, population, and economic size, smart cities and communities are focusing on improving the lives of their residents and visitors. This core value is a unifying factor bringing together all stakeholders and citizens on a smart city's journey. Fig. 1 below illustrates this perspective, presenting multiple views in which a city can be studied and characterized.

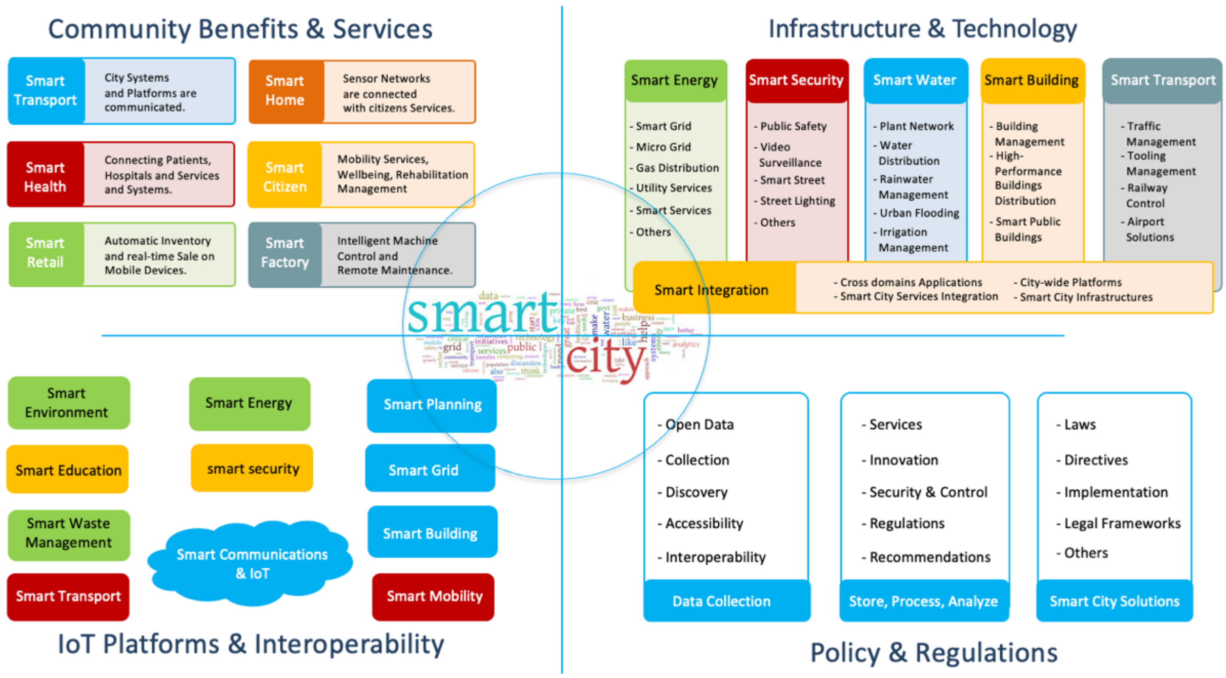

Figure 1 – Smart City Perspectives

3. Overview of Conventional Smart City KPI Approaches

Technology	KPI Metric	Platforms	Services	City Applications
Sensors	• Sensors per area • Sensors per system • Sensors per capita	• Traffic management system • Air quality monitoring	• Smart parking • Air quality and weather conditions	• Traffic • Noise • Air quality • Other
Wireless Networks	• Network utilization • Access points per area • Access points per capita	• WiFi network • Sensor network • 5G network • Fiber optic LAN	• WiFi hot spot • Municipality services • City kiosk services	• Citizen services • Mobility • Infrastructure management

Technology	KPI Metric	Platforms	Services	City Applications
Data	• Data volume • Number downloads • Upload/download speeds	• City data database • City data analytics	• City data portal • Electronic voting services	• Data Management • Storage • Access • Fusion

The use of KPIs in cities is a common practice, with well-known generic indicators for evaluating and measuring today's smart city ecosystems. Table 1 above provides examples of notional output-based smart city KPIs for various technologies.

Examples of conventional outcomes-based KPIs for various community services include the following.

Table 2. Examples of Outcome-Based KPIs

Service	KPI Metric	Platforms	City Applications
Parking	Search time	Traffic management system	Smart parking
Traffic	Vehicles per minute	Parking management system	Smart traffic
Air quality	Health alerts	Air quality monitoring	Public Health
WiFi access	Use of online services	WiFi network	Online city services

Figure 2 displays many of the KPIs common to cities with efforts aimed at measuring outcomes.

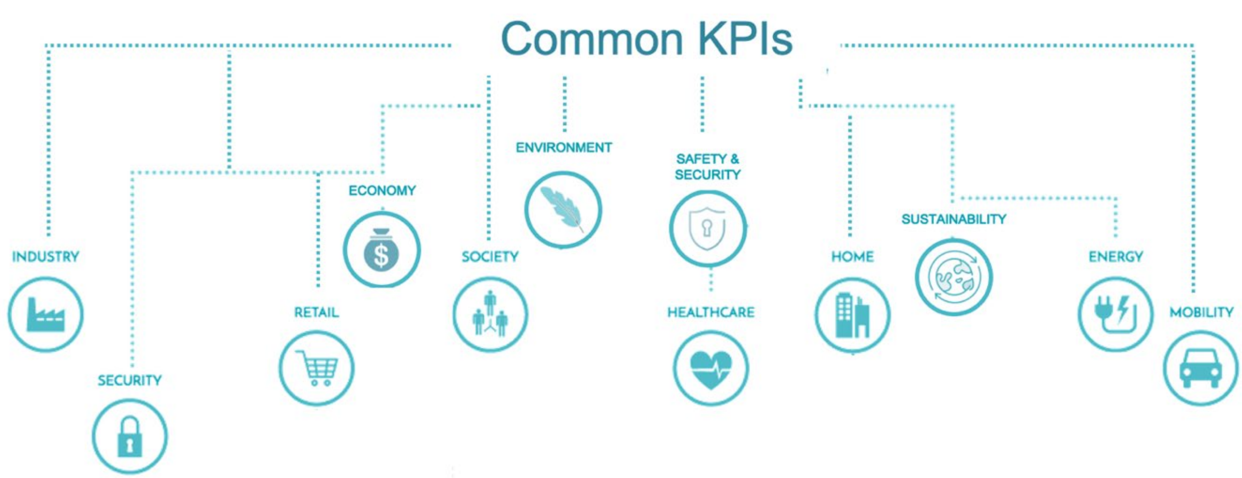

Figure 2 – Examples of Outcome-Focused KPIs

While these conventional KPI approaches are useful in managing smart city efforts, there are intrinsic limitations that can be summarized as follows.

- Smart cities have traditionally used metrics based on a particular deployed technology or service as a way to measure impact. For example, if a city deploys smart street lighting technology and traffic monitoring systems, associated metrics might include energy cost savings and congestion reduction. However, these direct-results metrics do not capture indirect benefits such as reductions in accidents and crime that make communities and inhabitants feel safer [10][11].
- Smart cities often use domain-specific KPIs focused on vertical sectors, with the goal of evaluating specific components of the city infrastructure, community services, or technologies [12]. For example, metrics for utility cost savings with the deployment of smart meters do not measure the benefits of increased engagement of citizens in sustainability initiatives resulting from increased awareness of their own energy consumption patterns.
- Cities deploy smart city platforms and provide community services based mainly on their unique infrastructure capacities and, to the degree feasible, by following generic KPI objectives. This results in cities having the same or similar KPIs with differing infrastructure-based evaluations, leading to uncertainty in identifying overall best practices for evaluation and assessment.
- Smart city IoT deployments tend to form technology silos, which result in information and application fragmentation. There is a need for increased interoperability across different deployments, which could enable repurposing and reusing IoT infrastructures for increased reach and overall impact. KPIs for interoperability and scalability are currently lacking but can be helpful in identifying silos.
- Despite successful IoT business cases in smart cities, there are not enough mature business models to ensure the uptake and wider use of IoT solutions. KPI-based assessment of the maturity of these models would help inform city leaders and motivate innovators in relevant IoT ecosystems.
- It is often difficult to replicate successful IoT solutions in other cities. Deploying IoT solutions requires significant customization effort, mainly because it is done in an ad hoc manner according to unique city conditions, and there is a lack of best practices because there are few clearly defined common objectives. KPIs can be used to incentivize replicability and best practices in using common KPIs, bearing in mind that cities always have different contextual situations for KPI implementation.
- A general practice in smart cities is to use KPIs to evaluate a smart city’s readiness level. However, KPIs may be related to local conditions that are often difficult to replicate in different cities. Likewise, the use of conventional KPIs is not equally applicable across different cities, and sometimes not even within different areas of a city; thus, a more holistic strategy is needed to provide meaningful readiness measures.

These limitations are illustrated in Fig. 3 below, which emphasizes the complex landscape of siloed, technology-centric, and domain-specific metrics that can emerge in applying conventional KPI approaches. In this figure, KPIs are represented in the same colors but in different sizes to depict the diversity of smart city systems in which a given KPI is used. For example, the number of downloads is often used as a metric for effectiveness of a mobile application although the results cannot be directly compared for an application used by employees within a city department as opposed to one intended for use by all residents. The image also depicts KPIs of the same size but different colors to represent the current tendency to replicate and use the same metric (e.g., number of deployed sensors) to address different problems. There are many benefits in using conventional KPIs in smart cities, but benefits may be reduced if there are varying ways of using and interpreting the same KPIs, or if there is a lack of a common understanding of smart city approaches and metrics based on different smart city standards [6][10] that appear to be proliferating.

Figure 3 – Conventional Smart City KPIs

Because there is often not a reliable and objective way to self-assess the level of success or impact that technologies have on inhabitants, technology deployments in smart cities are often limited to vertical applications and use cases with specific goals, rather than city-wide transformational goals. While there are ways to measure the number of solutions, services, and technologies deployed, cities cannot easily take advantage of the full transformative power of technology and smart services if technology deployments are seen only as building blocks for specific applications, rather than enablers for open innovation across city applications.

4. Elements of an Effective KPI Methodology

4.1. Goal

The goal in developing an H-KPI Framework is to build on conventional KPI methods to create a more holistic approach with integrated KPIs that facilitate self-assessment, strategic planning, and implementation. Figure 4 below illustrates this goal with conventional methods on the left and the H-KPI approach on the right. This comparison emphasizes that the H-KPI approach provides a comprehensive view and avoids fragmentation, enables aggregation and normalization of smart city indicators, and the underlying methodology – the H-KPI Framework – is applicable to different cities and communities, regardless of their size, location, and other characteristics.

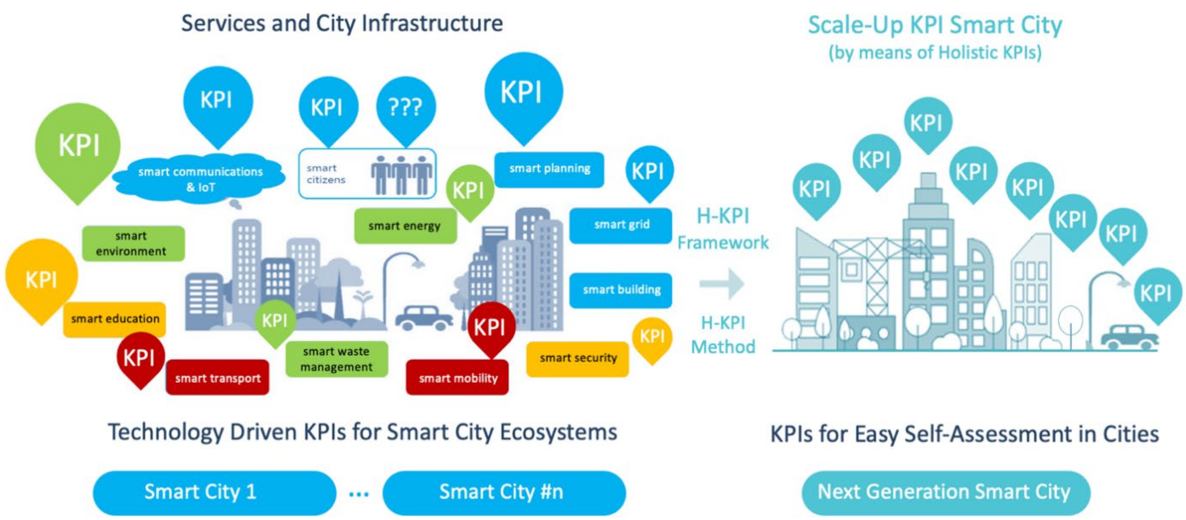

Figure 4 – Vision for Smart City KPIs

4.2. Implementation: Embracing Unique City Characteristics

A key element of the H-KPI approach is that while many cities and communities may share high-level goals – such as mobility, sustainability, and economic vitality – each is unique when considering the details of geography, economy, social and cultural settings, infrastructure, and more. This means that effective measurement strategies must not be one-size-fits-all. To be useful to city and community leaders and residents alike, the H-KPI Framework is designed to embrace the uniqueness of each particular community. The variables in city and community characteristics considered in this measurement methodology include the following.

4.2.1. Districts and Neighborhoods

Cities are geographic entities with identified boundaries, and often consist of multiple regions or territories. An example is a financial district within a well-delimited area but with different characteristics based on different business types, inhabitants, and service needs as compared to other regions. Applying the same KPIs and metrics to a financial district as to an arts and entertainment, government, or residential district is ill-suited to measuring performance against the distinct needs, expectations, and opportunities intrinsic to differing districts. City and community models that accommodate the diversity of districts are essential to smart city measurement methods.

4.2.2. Population and Economic Scale

In the past, generic KPIs have typically been generated and used to characterize a given city. Recently, with the introduction of emerging internet-connected technologies and improved quantification and monitoring capabilities, a more holistic model is possible. This is particularly useful when quantification is required for smart-region applications, such as regional disaster response. An example is a city, similar to another based on its geographic dimensions or characteristics, but differing in its population, culture, and commercial activities, which requires a tailored and holistic approach to KPIs to ensure the success of a coordinated, regional response. An effective smart city or community strategy depends on such factors as the city's geography, the distribution of services and infrastructures, and the number and activities of inhabitants in the various districts.

4.2.3. Previously Deployed Technologies

Cities and communities also differ in the state of currently deployed technologies, including breadth of broadband access, presence and extent of sensor networks, and degree of access to data streams and repositories. A holistic measurement approach must consider this variation in technologies, including across the following three characteristics.

4.2.3.1. Data

IoT technologies are changing how smart city services are organized, deployed, and maintained, from a very simple network of devices facilitating people's mobility by indicating better routes and traffic conditions, to more complex applications in which services are harmonized across sectors (e.g., bike sharing and public transportation planning and balancing). Data provide the means by which services are implemented and managed, and variation in degrees of data access, interoperability, and quality must be considered in designing effective measurement strategies.

Existing IoT data models vary widely in how data is collected and manipulated and how it is accessed. In this context, a particular problem is to define how to achieve broader access to the data. A common approach is using application program interfaces to enable shared use of the data and to providing cross-optimization capabilities through data exchanges. The H-KPIs Framework provides an approach for considering not only local and overall available data, but also the community's needs and priorities.

4.2.3.2. Digital Systems: Platform Interoperability and Connectivity

The latest developments in IoT solutions for a city rely on providing user services that are interconnected. Behind those interconnected services, there is a series of systems or platforms that enable interoperation amongst the different technologies, protocols, and formats. Note that in this report, a platform is defined as an information technology system focused on aggregation to provide broad access to data. Providing a means for measuring the role of data platforms in providing for efficiency in addressing smart city priorities is a key element of the H-KPI methodology.

4.2.3.3. Physical Systems: Sensors and Actuators

IoT is generally considered a baseline technology for smart city projects, with control systems linked to sensors and actuators in engineered systems for managing traffic, water, energy, communications, transportation, emergency response, and more. Current KPI approaches typically consider these systems separately, although there are extensive interactions and interdependencies. For example, transportation management is essential to effective emergency response; energy systems are often among the largest consumers of water, etc. The H-KPI methodology is designed to include these interactions and interdependencies.

5. Objectives and Approach

5.1. From Conventional KPIs to H-KPIs for Smart Cities

The H-KPI approach is intended to provide a reliable methodology for assessing technology and associated community benefits in smart cities [13][14]. A holistic model provides a means for a more comprehensive and integrated assessment of technical and operational performance in smart city IoT deployments [15][16][17].

Figure 5 – Overall Objective for Smart City H-KPIs

5.2. Objectives

The primary objectives in developing the H-KPI methodology are the following.

Objective 1: Integration. The approach must go beyond conventional baseline reference KPIs to integrate measurements across sectors, infrastructures, priority areas, and other dimensions that are characteristic of a given city or community.

Objective 2: Applicability. The approach must be applicable across a wide range of city and community types, service and infrastructure sectors, technologies, and applications. The objective is to provide a method that is useable across the diverse smart city and community sector. This applicability objective also allows for reliable self-assessment in which a community can level-set in comparison to other cities and communities by using a consistent methodology while also taking into account the unique characteristics of each community.

Objective 3: Extensibility. H-KPIs are intended to support the reuse and repurposing of infrastructures, services, and datasets, along with the integration of new technologies to keep pace with the rapidly evolving digital innovation landscape.

5.3. Approach

This section provides a broad overview of the H-KPIs approach, describing underlying assumptions, intended outcomes, and interactions between levels.

5.3.1. Baseline Assumptions

The Municipal IoT Blueprint (NIST Global City Teams Challenge [18]) describes the following baseline assumptions, which were adapted for use in designing the H-KPIs approach.

- **Each city is unique.** There is no "one size fits all" option that works across all different use cases and municipalities.
- **The "best fit" KPIs are a point-in-time decision.** KPIs that are relevant today may not be suitable tomorrow and, as the community progresses and technologies improve, the selected KPIs may need to be revised and updated.
- **There is no perfect KPI set for any particular situation**. The KPI selection process is an exercise in trading off multiple pros and cons among the various options.

5.3.2. Intended Outcomes

The following are the intended outcomes in using the H-KPI Framework:

- **Simplify options to identify and use common city KPIs.**

  H-KPIs are intended to be used as a reference framework and build on interoperability and the inclusion, where possible, of standards-based technologies.

- **Provide a replicable method for self-assessment tailored to a city or community's needs.**

  By combining tailored KPI selection with a quantifiable weighting approach for direct and indirect metrics, the approach allows the various community stakeholders to compare assessments.

- **Facilitate alignment of city and community goals.**

  By considering the interactions between technologies, infrastructures, and applications, the approach is intended to help cities and communities manage multiple parallel or sequential smart city projects that may cross sectors and span multiple goals.

5.3.3. Cybersecurity and Data Protection

Security and privacy protections are key goals for smart city systems that are used to control critical infrastructures or house sensitive data. A comprehensive KPI methodology must include assessment of cybersecurity and privacy protection provisions across all relevant aspects, including technologies, platforms, sectors, and levels. The H-KPI method makes the quantification and assessment of cybersecurity and data protection indicators more objective by identifying the different relationships (direct or indirect) across these various aspects.

5.3.4. Maturity Level

A common application of self-assessment methodologies is enabling cities to conduct a reliable maturity assessment. Such assessments involve comparing the current state of technology of a given city or community to a maturity model describing the spectrum of comparative readiness states, from beginning stages of technology adoption to highly advanced states. These assessments enable cities and communities to set realistic goals for smart city projects that are feasible, while also providing incremental advances in overall maturity. A number of smart city maturity models have been proposed to enable such assessments [19]. These models are often organized around dimensions of infrastructure and service sectors, or city functions. Conventional KPI approaches enable a dimension-by-dimension assessment but may not include benefits and applications at a higher level or interactions across dimensions and levels. The H-KPI approach provides a means for addressing this gap.

6. Components of the H-KPI Method

This section describes the H-KPIs methodology and provides definitions of relevant terms and a description of each of the steps in the method.

6.1. Levels of Analysis

A novel element of the H-KPI method is the assessment of data at three interacting levels of analysis – technologies, infrastructure services, and community benefits. These levels are depicted in Fig. 6 below and are summarized in the text that follows.

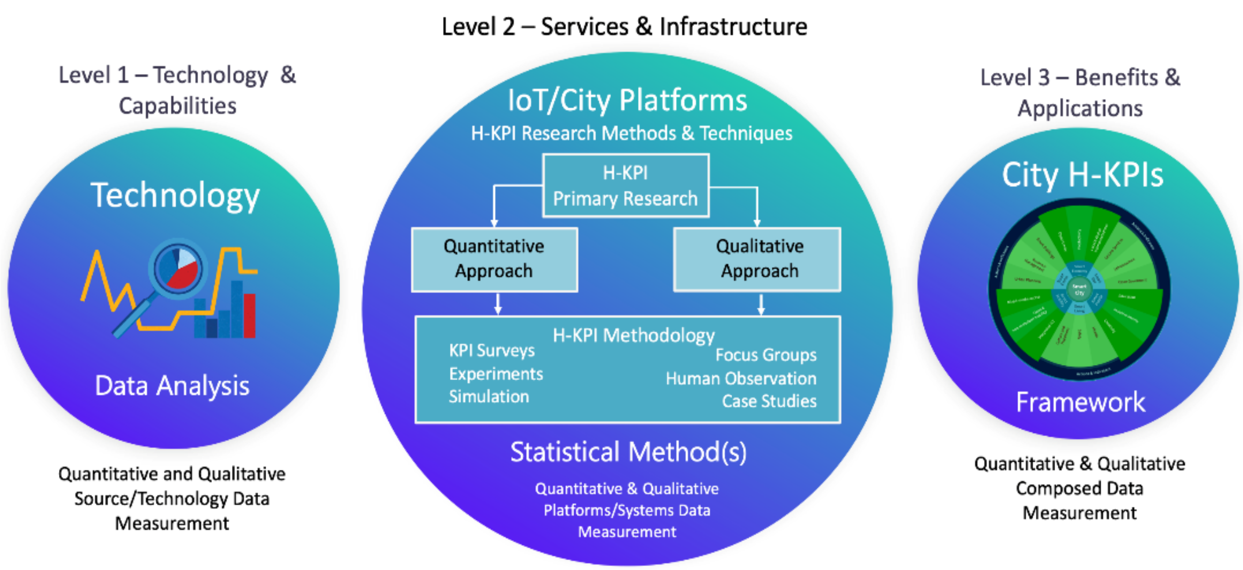

Figure 6 – Levels of Analysis

6.1.1. Level 1 – Technologies

Level 1 focuses on enabling technologies and their core capabilities. Examples of technologies include sensors and actuators, networks, data systems, and computational hardware and software systems. Examples of core characteristics are the elements of trustworthiness – security, privacy, resilience, reliability, and safety. Data analytics at this level focus on technology and service metrics such as network capacity, sensor accuracy and coverage, system downtime and recovery, conformance with security and privacy guidance, etc.

Figure 7 below shows examples of Level 1 technologies and capabilities. In many smart city implementations, Level 1 components provide both data inputs and essential functionality (such as network services) for one or more IoT platforms (indicated by bar at the top of the figure) that serve to integrate data and systems for access at higher levels. Thus, effective performance metrics at Level 1 must go beyond just the number of deployments to include data use, re-use, coverage, and quality; alignment to prioritized community use cases; and support for infrastructure management, city operations, and applications that benefit residents. The H-KPIs approach is intended to support these extended metrics.

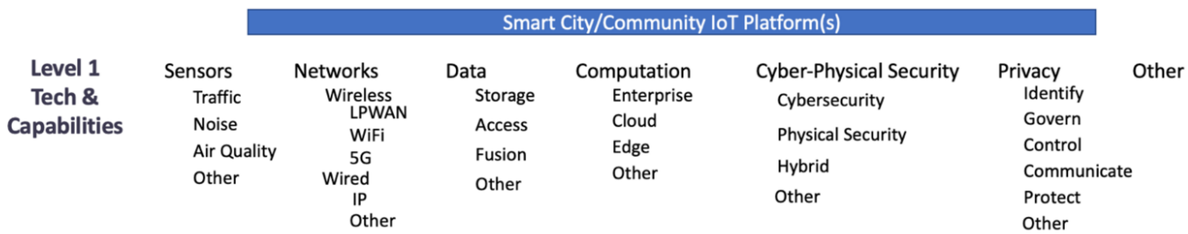

Figure 7 – Level 1 Examples

6.1.2. **Level 2 – Infrastructure Services**

Level 2 is centered on the infrastructure services that enable a city or community to function. Infrastructures include those in the communications, transportation, energy, water, and buildings sectors, which range from roads and bridges to networks, pipelines, electric grids, and commercial and residential structures. Key services include emergency response and law enforcement, waste management, education, and city/community services. Data analytics at this level are centered on measures of infrastructure functions, such as broadband access and public transit use, and on service effectiveness, such as emergency response time and access to education.

Figure 8 shows examples of Level 2 infrastructure services. These services may interact with both IoT platforms connected to Level 1 (bar at the bottom of the figure) and services platforms that support Level 3 functions (bar at the top of the figure). Performance metrics at this level must take into account differing levels of technological maturity across the various services and infrastructures; acknowledge the role of different owners, operators, and customers and accommodate their differing accountability and financial models; and include the interactions and interdependencies between the various services and infrastructure sectors.

Figure 8 – Level 2 Examples

6.1.3. **Level 3 – Community Benefits**

Level 3 focuses on applications that benefit people and businesses and on providing equitable access to those benefits. Examples include personal safety and security, business and jobs growth, health care, environmental quality, and other quality of life factors including arts and entertainment. Data and analytics at this level focus on the experiences of residents, visitors, and businesses throughout the city or community.

Figure 9 below shows examples of benefits and applications that are elements of Level 3. These elements depend on input from Level 2 services and infrastructures and may be connected to Level 2 via services platforms (bar at the bottom of the figure). Performance metrics at this level are human-centric and focus on factors such as quality of life, economic vitality, and personal health and security. This requires both objective and subjective measures of changes in the conditions of a city or the perceptions of its residents, including direct or indirect measures of the satisfaction of individuals using a particular service. Metrics must also take into account factors such as population and its demographic, geographic, and other attributes relevant to the goals of the smart city or community aspect under evaluation.

Figure 9 – Level 3 Examples

6.1.4. Interactions Between Levels

Assessing interactions across the three levels of analysis is a central component of the H-KPI methodology. Figure 10 below provides a graphic representation of this concept, with levels labeled at the left edge and interactions indicated by arrows. For example, roadside sensors deployed at Level 1 can contribute to multiple infrastructures at Level 2, such as traffic management, emergency response, and environmental monitoring. Thus, KPIs associated with a sensor deployment project must encompass all infrastructures that will use sensor data. Further, return-on-investment (ROI) analyses should include the value of benefits to all relevant infrastructures and not just to a designated primary application. In another example, the benefits of a project to improve public transit at Level 2 goes beyond just mobility benefits to include increased environmental sustainability, more equitable access to health care and jobs, and enhanced economic growth, as shown in Level 3. The KPIs selected for this effort and the corresponding ROI analyses should encompass all relevant Level 3 benefits and applications.

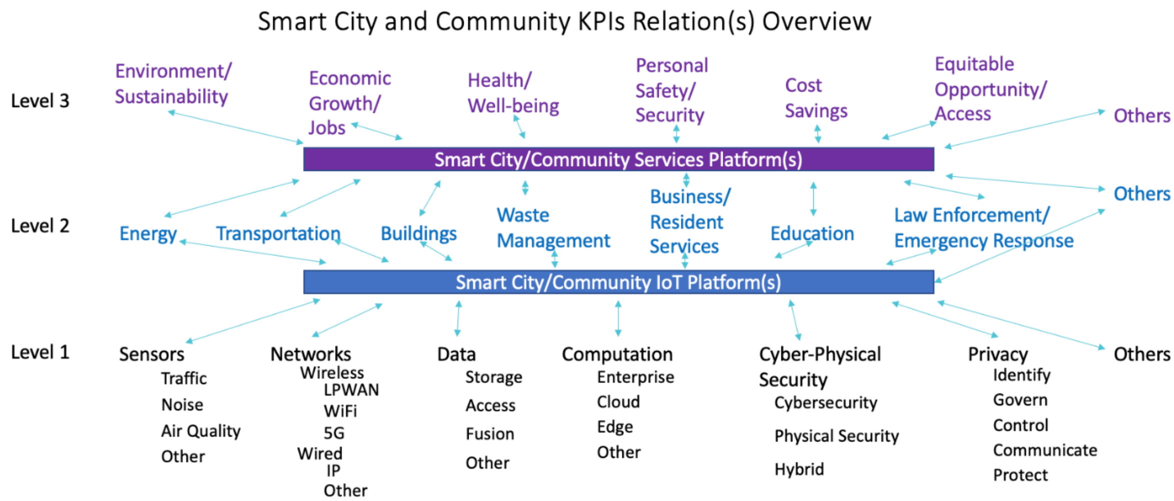

Figure 10 – Relationships and Interactions Between Levels

6.1.5. Data Relationships

A ***holistic relationship*** (referred to as 'relationship' below for brevity) is a discrete step in a data or information flow pathway. Each step consists of a source, path, and destination and may also involve reuse of data or information from another pathway. For purposes of analytics, a relationship is defined here as an n-tuple[1] of the general form (reuse$_{a\text{-}n}$; {source_type}, {path$_\alpha$}, {destination, processed data type → F(ID)}) (see Appendix D for details). A reuse specifies the relationships that provide data or information to the source from another pathway that is included in the specified transmittal. Sources include sensors, platforms, data stores, applications, etc. that are the origin for the data or information transmitted in a specified step. The path represents the means for transmission and may include wired or wireless networks, etc. The destination is the application, platform, data store, etc. receiving the transmitted data or information. The processed data type is the data model, taxonomy, etc. for data that has been processed at the destination and made available for use or further transmission. Processing (denoted by F) of input data (ID; i.e. data received by the destination from a source) to produce the processed data type is represented by F(ID). Thus, the expression "processed data type → F(ID)" allows full tracking of all data manipulations at all steps in an information flow pathway.

Two types of relationships – dependencies and connectors – are defined here and illustrated in Fig. 11 below, with each dependency shown by a numbered dark arrow and each connector by a light blue arrow with a letter designator. A ***dependency*** is a relationship in which there is no reuse of data or information from other pathways. For example, *dependency$_1$* at the bottom center of Fig. 11 is the set of sensors (source) sending data via an LPWAN network (path) to the destination 'Smart City/Community IoT Platform.' Thus, *dependency$_1$* is the tuple (nullset; {Sensor_HVAC Energy}, {LPWAN}, {IoT Platform, IoTP Energy -> F(HVAC Energy)}) . Dependencies may arise historically or through the sequencing of projects. For example, a dependency established in an early smart city project may provide data or information that can be made available for reuse in subsequent projects through connectors.

[1] In mathematics, a tuple is a finite ordered list (sequence) of elements. An *n*-tuple is a sequence (or ordered list) of *n* elements, where *n* is a non-negative integer.

A ***connector*** is a relationship that includes reuse of an existing source, service, or benefit for a new function or goal. For example, *connector*$_a$ (center right in the figure) is the flow of information from the smart city/community IoT platform via a network path to an air quality management service. The original source of information for *connector*$_a$ is *dependency*$_1$, i.e., this connector provides for re-use of the humidity and temperature data originally implemented for use by the building energy management service. Thus, for example, *connector*$_a$ in Fig. 11 is the tuple ({D2}; {IoT Platform_IoTP Humidity}, {Pathβ}, {AQM, AQM Humidity -> F(IoTP Humidity)}).

A ***service*** at Level 2 or ***benefit*** at Level 3 relies on a composition of relationships that can be described as an n-tuple of the dependencies and connectors that provide the required information flows. An example of a composed information flow enabling a Level 2 service is shown in Fig. 11 for Building Energy Management. The flow enabling this service can be represented by an n-tuple of dependencies; i.e. (*dependency*$_{1,2}$), where the ordering of the tuple is determined by the sequence of steps in the data/information flow. Building Energy Management, a Level 2 service in Fig. 11, can be represented by the n-tuple (*dependency*$_{1,2,3,4,5,6}$). Similarly, Air Quality Management is (*dependency*$_8$, *connector*$_{a,b}$). where the ordering within tuples is dependencies followed by connectors.

To summarize: the elements of a smart city system graph, such as the one shown in Fig. 11, can be summarized as follows. A relationship, represented by arrows, is a step in an information flow pathway with a discrete source, path, and destination. A dependency is a relationship in which the data are not reused from another information flow pathway. A connector is a relationship in which the data are reused from another pathway. A service or benefit, shown as labeled boxes, is represented by the set of relationships that deliver the required data. A platform, represented by bars, is a system that provides for aggregation and processing of data for broad distribution, but does not have a service or benefit function.

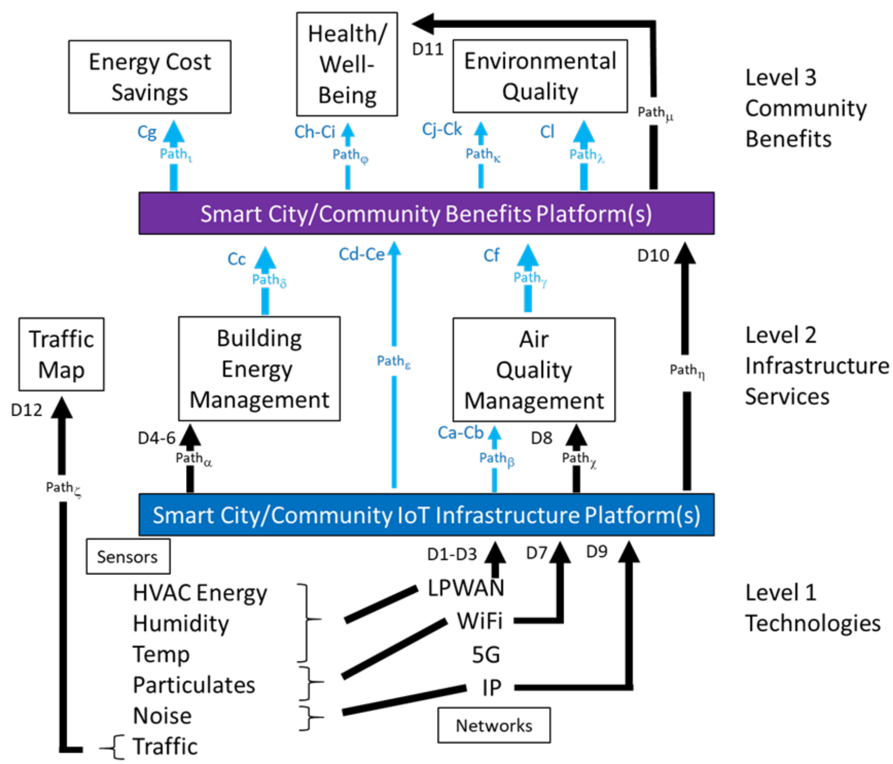

Figure 11 – Smart City Systems Graph

This approach allows any service or benefit to be described by ordered composition of the dependencies and connectors that make up the required information flows. Structured decomposition enables tracing of information flows from high level benefits all the way to original data sources (such as sensor sets), and vice versa. Tracing provides a means for analyzing complex failure or fault modes and for identifying interdependencies that may be affected by updates or other changes to individual information flows. Most importantly, as described below, the approach provides the basis for quantitative metrics for measuring 'smart' as used in the phrase 'smart cities and communities.'

6.2. Data Collection

The H-KPI method comprises five essential steps, including initial source selection, as summarized in Fig. 12 below. Each of these steps is described in more detail under the sub-headings that follow.

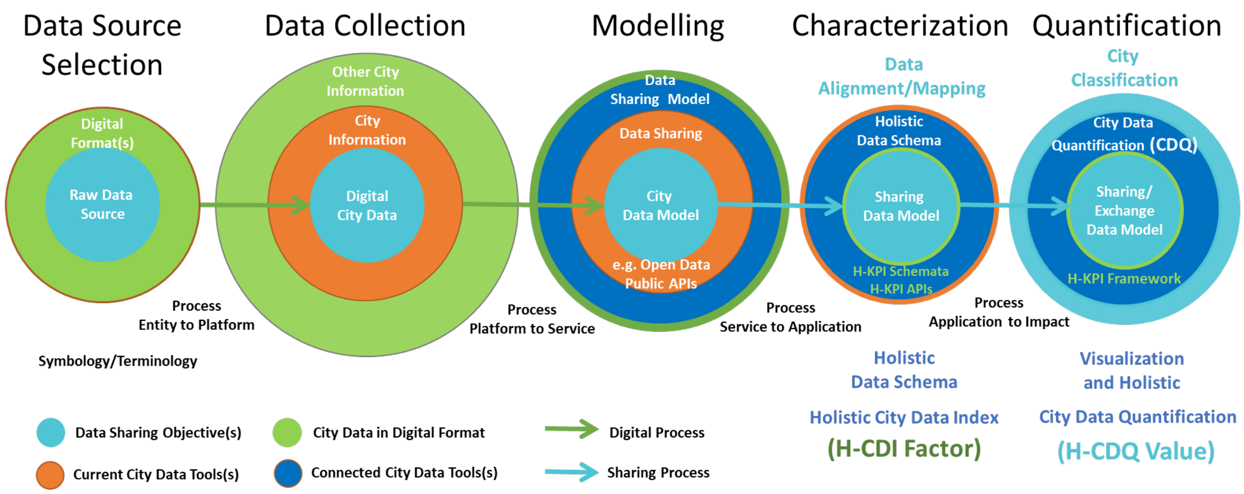

Figure 12 – H-KPIs Framework Measuring Model

6.2.1. Step 1, Data Source Selection: Define City Data Sources

The selection of city KPIs is dependent on each city's plans and goals. To identify data sources, a city or community must examine not only individual technologies at Level 1 (such as sensors), but also the platforms, systems and services at Level 2, and other data sources relevant to community benefits at Level 3. Figure 13 below represents city data as raw data sources and its digital formats in concentric circles. The combination of raw data source and digital format enables subsequent processing by platforms or systems (and is labeled '*digital city data*' in the description of the next step that follows). Note that the data sources relevant to a benefit, in effect, define how the benefit is operationalized. They, and the services that feed into the benefit are one way of understanding the abstract benefit.

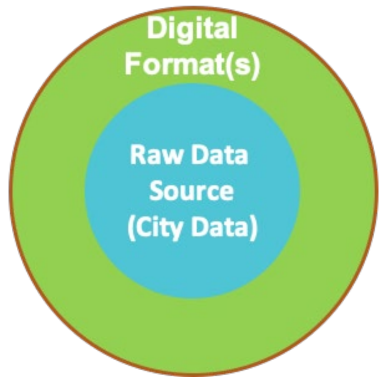

Figure 13 – Data Source Selection

6.2.2. Step 2, Data Collection: Turning Raw Data into Information

Figure 14 below shows a set of concentric circles representing the relevant data and information types. The inner circle represents the *digital city data* in a specified format (e.g., as .xml, or .json files). The next level is *city information* and comprises information that has been derived from a relevant data type for a particular city. Other cities' information is represented in the figure as the outermost circle and includes information that may be useful for purposes of comparison.

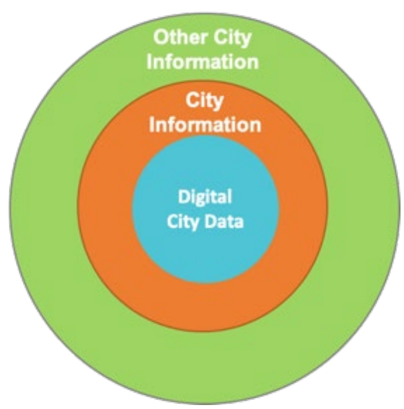

Figure 14 – Data Collection

6.2.3. Step 3, Modeling: Development of Data Sharing Models for City Data

The set of all digital city data form a city *data model*. Figure 15 illustrates the overall data modeling strategy. As data sources are identified or implemented, an overall city data model (center circle in the figure) should be developed and revised as needed to accommodate the various formats. Requirements for shared data (next layer in the figure) should then be applied in developing a data sharing model. The outside green circle represents other smart city data sharing models that may need to be considered for regional or other multi-city/multi-community purposes.

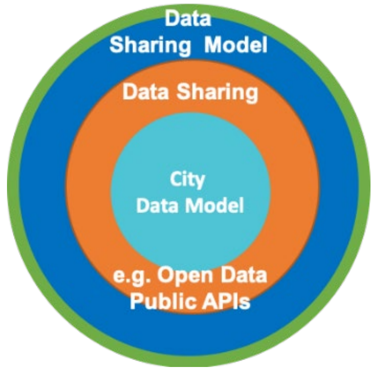

Figure 15 – Data Modeling

6.2.4. Step 4, Characterization: Cataloging Smart City Data and Goals

Figure 16 below illustrates how the holistic method is implemented using a data schema that allows linking data and information flows to KPIs and city goals. This step focuses on cataloging the identified data and information flows in three ways. The first is a catalog of all of the relationships identified in the previous steps, including all dependencies and connectors across all three levels of analysis (see section 6.1). The resulting catalog is a listing of n-tuples corresponding to the complete set of dependencies and connectors. The second catalog links KPIs to the relevant dependencies and connectors. For example, dependencies for data flow from traffic sensors to an automated traffic management system would be linked in this catalog to a KPI for reduced traffic congestion. The third catalog is a listing of the community's smart city goals, with associated priority rankings. An example of a priority ranking system might be that for a city with three smart city goals – improved public health, increased mobility, and enhanced sustainability – where sustainability is the highest priority, and health and mobility are lower but equal priorities. The corresponding ranking factors might be: sustainability = 0.5, health = 0.25, and mobility = 0.25. While each city or community will develop its own priority ranking approach, the result should be numerical values for which the sum of the specified set of priority rankings is one (see Section 7 below).

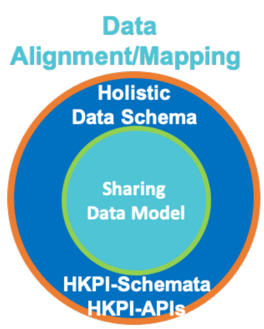

Figure 16 – Data Alignments

6.2.5. Step 5, H-KPI Quantification

The final step, H-KPI quantification, is illustrated in Fig. 17 below. This step involves comprehensive analysis of the information gathered in steps one through four using the metrics of the H-KPI framework described in Section 7 below. The results of this analysis provide a means for a city or community to self-assess their current smart-city maturity level, prioritize projects, enhance existing systems, manage systems operations, provide for systems resilience, and develop comprehensive plans toward smart city/community goals as described in Section 8 below.

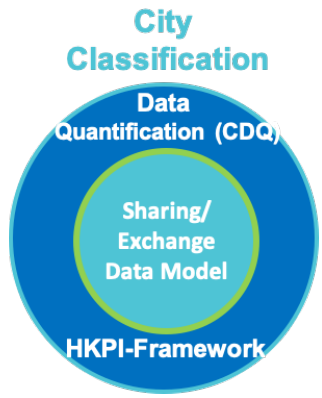

Figure 17 – H-KPIs Quantification

7. H-KPI Framework: Measuring 'Smart' in 'Smart Cities and Communities'

The H-KPI Framework is a measurement methodology for objectively self-assessing the level of 'smart' for any smart city or community. The methodology is intended for use at multiple levels in a smart city or community landscape. For this purpose, the concept of an *Element* is introduced. An *Element* may be specified at any desired level of analysis, including the neighborhoods or districts that make up a community, departments within city government, economic sectors across a city, communities across a region, etc. This approach facilitates smart city planning and management that meets different needs for different districts or sectors, provides equitable access to services and benefits, identifies gaps and opportunities in current implementations, and optimizes smart city/community investments.

For purposes of this H-KPI Framework, 'smart' as used in 'smart city/community' is defined as:

> *The efficient and effective use of digital technologies to provide prioritized, high-quality infrastructure services and community benefits.*

The H-KPI measurement framework focuses on the key elements of this definition and assesses efficiency, effectiveness, quality, and alignment with priorities. The Framework comprises five metrics:

1. alignment of community priorities within and across elements;
2. investment alignment with community priorities;
3. investment efficiency;
4. information flow density; and
5. quality of infrastructure services and community benefits.

The measurement methods for each of these metrics are outlined in the text below and described in detail in Appendix D. For each method, the results can be presented in the general form of a table as shown in Table 3 below.

Table 3. Results

	Element_1	Element_2	…	Element_n
KPI_1				
KPI_2				
…				
KPI_m				

Once completed, the data in these tables can be used to calculate numerical indexes through statistical, matrix, or array operations that allow objective comparisons among priorities, within and between cities and communities, across different architectures and technologies, etc. Some examples of simple operations on the data are described in the text below and in an appendix. More advanced operations will be described in follow-on publications.

7.1. Metric 1: Alignment of KPIs With Community Priorities Elements

A smart city or community may set multiple goals for itself. For example, a community may seek to use digital technologies to increase economic growth, improve public health, and enhance environmental sustainability. For smart planning, these goals should be prioritized to guide the overall allocation of resources.

To measure progress toward each of its goals, the community may have multiple KPIs, each associated with a specific goal. To guide resource allocation and management, the overall prioritization among KPIs should align with the overall prioritization of goals. However, individual elements within a community, such as districts or neighborhoods, may have differing needs between and within goals. For example, a goal to increase economic growth may translate into KPIs for infrastructure capacity in a business district and educational opportunity for a residential district. Furthermore, the residential district may set public health as its top priority while the business district may set economic growth at the top. Tailoring of KPIs to meet the needs of specific elements can be a strength of a smart city or community plan if it is effectively managed. On the other hand, it can be a weakness if unmanaged and can lead to misalignment of resources with overall community goals and priorities.

The first metric focuses on managing the alignment of element-level KPIs with overall community goals and priorities, and is described in detail in Appendix D. The method allows for tracking priority factors at the element level and assessing the degree to which these factors collectively align with overall community goals. The result of the analysis is a Priority Factor Alignment Index – the closer the alignment, the greater the numerical value of the Index. Tracking this index can allow communities to optimize resources in ways that meet distinct needs while remaining aligned with overall goals. This index, then, provides one measure of how comparatively 'smart' a smart city or community strategy may be.

For illustration purposes, Table 4 below shows a hypothetical example of priority factors in an imaginary city of six districts with six KPIs. This table is shown in the same form as Table 3 above for comparison. The general method with associated calculations can be found in Appendix D. In this example, each district has assigned its own priority factors to each KPI such that its factors add up to 1; the priority factor for each KPI averaged over the 6 Districts is found in the next-to-last column on the right. Similarly, city-wide leadership has assigned its own overall priority factors to each KPI in the last column on the right. A comparison of the final two columns provides a measure of the degree to which the priorities set individually by the districts collectively align with the priorities set city-wide.

Table 4. Priority Factor Alignment Example

	District$_1$	District$_2$	District$_3$	District$_4$	District$_5$	District$_6$	Priority Factor Roll-up	City-Level Priority Factors
KPI 1	0.3	0	0.1	0.4	0.9	0	0.28	0.1
KPI 2	0	0.2	0	0.1	0.1	0	0.07	0.15
KPI 3	0	0	0	0.1	0	0.5	0.10	0.05
KPI 4	0.5	0.2	0.7	0.25	0	0	0.28	0.22
KPI 5	0.2	0	0.1	0	0	0.5	0.13	0.14
KPI 6	0	0.6	0.1	0.15	0	0	0.14	0.06
Sum	1	1	1	1	1	1	1	1

7.2. Metric 2: Investment Alignment with Community Priorities

The second metric takes the first metric one step further. It focuses on the degree to which investments across elements collectively align with community priorities. This approach recognizes that an investment in infrastructure capacity in a business district and in educational opportunities in a residential district may both contribute to a goal for economic growth. However, while economic growth may be the first priority for the business district, it may not be for the residential district. Thus, these investments should not be treated identically in assessing alignment with overall goals.

Appendix D describes an approach for measuring the alignment of investments with community priorities. The method provides, for each KPI in each element, a measure of the alignment of the investment with the element-level priority factor. Specifically, it reflects the degree to which the distribution of investments across KPIs and elements aligns with the distribution of priorities. The method also allows for assessing the effectiveness of the distribution of investments for a given KPI across all elements. For example, in pursuing an economic growth KPI, investments in infrastructure capacity might be greater in business than in residential districts, with the inverse indicated for investments in educational opportunities.

The method also allows for generating an alignment index for all KPIs across all elements. For example, this index provides an indicator of how well the set of all investments are meeting the needs of specific districts while staying aligned with overall community priorities. Higher index values are indicative of better alignment, another measure of how 'smart' a smart city or community strategy may be.

7.3. Metric 3: Investment Efficiency

The third metric addresses cost efficiency for technology investments. As shown in Appendix D, the units in this measurement are information flows per dollar, euro, or other monetary unit. Data reuse, or multiple uses for a given data stream, through connectors that tap into data flows via existing dependencies is an important means for increasing efficiency through smart technology planning. A platform-based architecture that enables broad access by applications to multiple data streams can significantly facilitate the implementation of connectors that enhance efficiency.

This metric can be useful in smart city planning where a goal may be to maximize the impact of limited resources. An investment efficiency factor can be calculated for each KPI in each element, allowing comparative assessment of efficiency for a specified KPI-based goal in each district or neighborhood. A mean efficiency factor can be calculated for a given KPI across all elements, allowing comparative assessment of the impact of pursuing different KPI-based goals. And an overall efficiency index can be calculated for all KPIs across all elements. The higher the value of this index, the greater the overall efficiency of investments for a given smart city or community.

7.4. Metric 4: Information Flow Density

The essence of a smart city or community lies in mobilizing information for use in enhancing infrastructure services and creating community benefits. However, it is not the total number of information flows that make a city or community 'smart,' since a large city would normally be expected to have more than a small town or community. Further, the number of information flows in a business district is subject to different factors than those for a residential neighborhood. To enable meaningful comparisons, the fourth metric, shown in Appendix D, provides for normalizing to relevant density factors (e.g., per capita) to account for different population sizes, per square kilometer for different areas, per unit GDP for different size economies, etc. The selection of density factor is left to the individual self-assessment but should be relevant to the comparison under consideration. For example, if the focus is on public health, then a per capita density factor may be appropriate. But if the focus is on economic growth, then a per unit GDP factor might be selected.

A key goal of many smart city or community efforts is equity in access to the benefits of those efforts. The information flow density metric, when expressed on a per demographic unit, per neighborhood, per sector, or other relevant basis can provide one means for assessing equity in the design and implementation of one or more smart city or community efforts.

This fourth metric provides a means for assessing information flow density for each KPI in each element, for a given KPI across all elements, or as an overall index for all KPIs across all elements. In each case, higher values are an indicator of 'smartness' for the smart city or community examples being considered.

7.5. Metric 5: Quality Factor

The fifth metric goes beyond assessing the number or density of information flows to providing for evaluating performance quality for the corresponding infrastructure services or community benefits. The method is based on evaluation of service or benefit performance data for a given KPI in a specified element. Examples of performance data might include energy use data for a building energy management system or user surveys for an online citizen services portal. The resulting quality factors and index are a measure of not only how well a given service or benefit meets performance targets on average, but how much an individual data point may vary from the target.

The method shown in Appendix D is based on comparison of actual performance data to targets set for a given KPI-based service or benefit. While the example in the appendix implements the Six Sigma method, other statistical or subjective quality assessment methods may be used for this metric.

This metric provides another input to an assessment of equity in implementation for a smart city or community effort by enabling a neighborhood-level or demographic-specific assessment. For example, a community that on average meets its public health targets but with widely different results for different neighborhoods would have a lower quality index than another community in which not only the average is on target, but similar outcomes are found across all neighborhoods. Thus, a higher quality index on a by-neighborhood or by-demographic comparison can be an indicator of higher equity.

8. Applying the H-KPI Method

The H-KPI Framework provides five core indices for self-assessing 'smartness' in a smart city or community example: priority factor alignment (P), investment alignment (IA), investment efficiency (IE), information flow density (DI), and quality (Q). While individual communities may choose to place greater emphasis on one or another of these indices, these measurements can also be considered collectively for an overall self-assessment analogous to a five-star rating system.

Note that additional metrics can be added as needed using the same underlying methodology. Additionally, the methodology lends itself to more complex assessments of interactions across metrics using methods from statistics, group theory, and array or matrix operations as described in Appendices D and E.

While the H-KPI method can be applied to a variety of domains where holistic measuring is required, two examples of applying the H-KPI approach in smart cities and communities are provided below.

8.1. Strategic Planning

The first example is the use of the H-KPI method throughout the various phases of smart city and community strategic planning. Figure 18 below provides an overall view of the role of H-KPI modeling in the planning process.

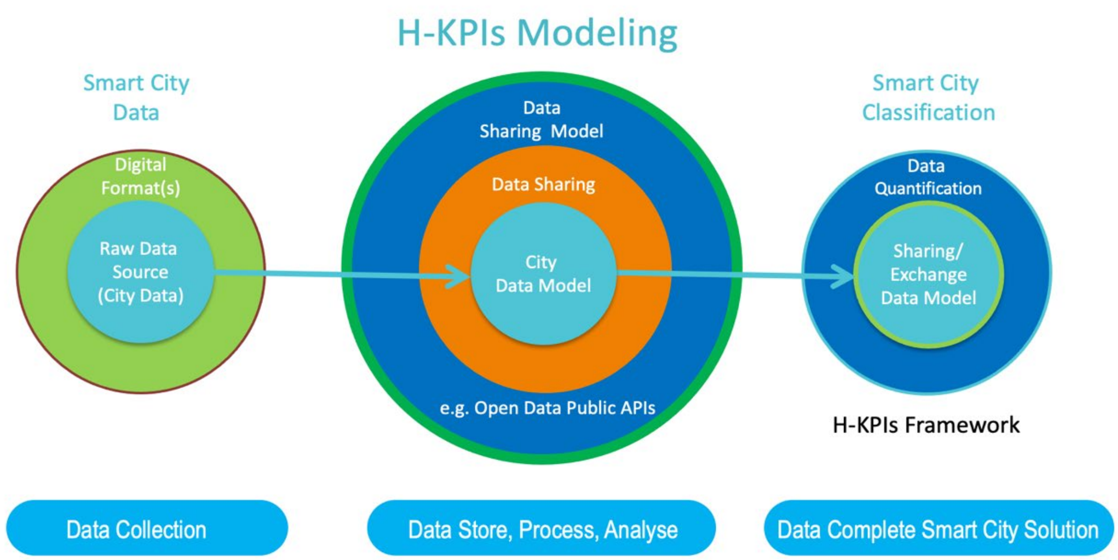

Figure 18 – Smart City Data and Information Flow

The first step in developing or revising a smart city or community strategic plan is conducting a baseline assessment, including evaluating the current maturity level [19]. The H-KPI method facilitates this baseline assessment in several ways. First, it provides a structured means for producing a comprehensive inventory of existing technology deployments – i.e., a catalog of the currently available data sources, data models, network connections, platform resources, etc. Second, it provides a means for not only cataloging existing performance indicators, but also linking them to current community goals and priorities. Third, it allows a meaningful comparison to other cities and communities to draw from relevant experience elsewhere. This includes the ability to adjust for the inevitable differences between the various cities and communities under comparison.

A second step in the strategic planning process is a comparative evaluation of options. The use of the H-KPI method in a 'what-if' mode enables a quantitative comparison of options in which each option can be modeled in the context of the complete system. These options may range from which infrastructure services or community benefits to prioritize, all the way to more detailed questions around the choice of specific technologies and commercial or custom applications, etc. The metrics for comparison go beyond overall cost comparisons to include efficiency of use of prior investments, alignment with community priorities, and effects across the various neighborhoods and districts.

Developing an effective systems architecture is another strategic planning step that is facilitated by the H-KPI method. The baseline assessment provides not only a catalog of deployed technologies, but also a directed graph to visualize the structure of existing information flows into which the new architecture will be placed. This approach helps communities make the most of previous investments, avoid siloed applications that are isolated from other city systems, and ensure the selected system actually works in the community when it is deployed.

The H-KPI method also facilitates assessment of the sequencing of smart city and community projects within a broader strategic plan. Those projects that will generate important data flows required by other projects can be readily visualized in the directed graph and sequenced early in the strategy. Projects that are well-aligned with immediate or time-sensitive community goals and priorities are identified by the method and can be prioritized for implementation. Projects that provide significant benefits for low costs because of efficient use of existing systems can also be prioritized.

These applications represent a few examples of the applications of the H-KPI method to strategic planning. Because of the systematic nature of the approach, the use of holistic metrics, and linkage to community goals and priorities, the method can support a wide range of applications in strategic planning.

8.2. Smart City and Community Operations

Scale and complexity are intrinsic characteristics of smart city and community systems. Contributors to complexity include the multi-technology, multi-protocol, multi-sector, and multi-user characteristics of smart city systems. A traffic management system includes many different types of sensors and networks that consume and generate a range of data types, which are used beyond just the transportation department to include public safety, first responders, city planning, environmental management, commuters, logistics companies, and other stakeholders. That same traffic management system must scale from individual intersections to road segments, city districts, and regional networks. Further, the traffic system must interact with other smart city and community systems focused on public health, mobility, and other services and benefits.

The H-KPI method provides a means for managing this scale and complexity because it is amenable to computational methods. This includes the use of n-tuples, directed graphs, matrix operations, statistical methods, and group theory. Fault tracing provides one example. With branched and tiered data flows serving an application at the community benefits level, loss of a data flow potentially can be caused by failures at multiple levels and sources. The H-KPI method provides a means for complete tracking of information flows at every step for automated monitoring and control applications.

Another example is in managing updates or replacements for existing systems. Replacing data processing systems at an intermediate level in a smart city technology ecosystem requires knowing all of the follow-on and end-user systems and their interdependencies. The H-KPI method provides a means for modeling those interdependencies to assess the impact of any proposed change.

The flip side of fault tracing is fall-back management. When a fault interrupts one data flow, being able to identify and implement alternatives is important to managing complex systems. This is especially important for managing critical systems for disaster and emergency response where resilience, including rapid recovery, are essential to the welfare of the community. The H-KPI method can support computational methods for fall-back management.

To illustrate the application of computational methods to smart city and community systems, Fig. 19 below provides an example of a functional architecture for a hypothetical data management scheme in a model city.

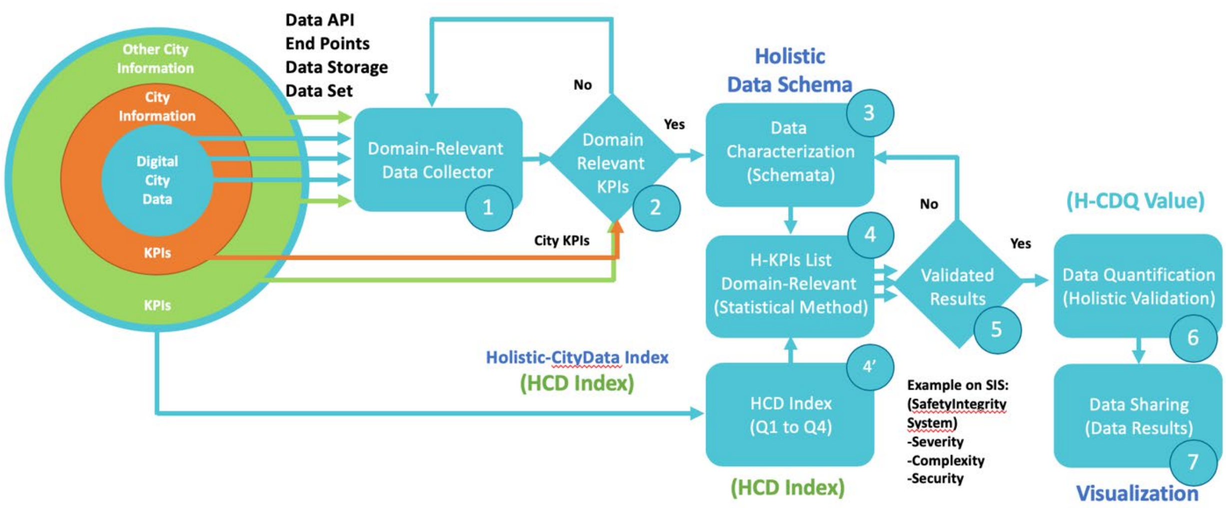

Figure 19 – Functional Architecture

Essential elements of this architecture are as follow.

1. The data collection and integration processes are activities related to the data sources available for the city under consideration. The domain-relevant data collector parses the digital city data into machine-readable files and passes the files as results.
2. The domain-relevant KPIs evaluation and verification process associates the received files with specific, selected KPIs, as appropriate. Relevant files are then passed forward to the data characterization process.

3. The data characterization process involves the storage of schemas for the possible relationships that may exist in a city and relates these to the associated KPIs. The schemas contained in this process are built using the H-KPIs method.
4. The H-KPIs re-alignment process is a statistical method based on defined weighting table according to the plans and priorities of the city or community. Note that this table is dynamic; it is updated as the needs and capabilities of a city or community evolve. The result can be an index (denoted in step 4' in the figure as Holistic City Data Index, or HCD Index) derived from the selected set of H-KPI metrics.
5. The validated results process verifies that the calculated value is in the expected range according to the relevant schemata and the defined weighting table.
6. The data quantification (holistic validation) process is a statistical operation following the propensity weighting method. The result of the quantification is a numerical value, identified in the figure for example as the Holistic City Data Quality Value (HCDQ).
7. The data sharing (data results) process is the visualization of the results of the analysis.

9. Conclusions

The H-KPI Framework builds on existing smart city and community KPI methods while addressing their limitations. The approach:

1. provides for comprehensive visualization and analysis of smart city systems;
2. enables quantitative self-assessment of performance metrics, including across different neighborhoods and districts, or among cities and communities with varying characteristics; and
3. supports computational methods, including automation of systems operations and management.

Challenges for future work include applying the method to current smart city and community systems and developing computational methods and tools, along with supporting systems. Collectively, this work is intended to enhance the ability of cities and communities to use advanced technologies efficiently and effectively in improving the quality of life for their inhabitants.

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Appendices

Appendix A. Acronyms/Abbreviations

5G	5th Generation Wireless Communications
AI	Artificial Intelligence
CDQ	City Data Quantification
COVID-19	Coronavirus Disease 2019
CPS	Cyber-Physical System(s)
EU	European Union
GCTC	Global City Teams Challenge
HCD	Holistic City Data
HCDQ	Holistic City Data Quantification
H-KPI	Holistic-Key Performance Indicator
HTML	Hypertext Markup Language
IoT	Internet of Things
IP	Inverse Probability
IT	Information Technology
KPI	Key Performance Indicator
LED	Light-Emitting Diode
NGI	Next-Generation Internet
NIST	National Institute of Standards and Technology
S&CC	Smart & Connected Communities
SP	Special Publication
U.S.	United States

Appendix B. Selected Smart City Use Cases and Data Characteristics

Smart City Service	**User Story**	**Technology Layer** (Example)	**Platform Layer** (Example)	**Community Layer**	**Infra-structure**	**Service** (Example)	**Application** (Example)
Smart Waste	As a city operator I would like to know when to dispatch garbage collection to improve efficiency and reduce unnecessary routes contributing to pollution.	YES (Bins Sensors Data)	YES (Trash Bin Data) (Collection Paths)	N/A	YES Subcon-tractor	YES (Best/ Optimal Routes)	YES (Operator and Citizen)
Connected Lighting	As a city operator I would like to have adaptive controls for my LED lighting in both the street and area environment to improve safety and energy efficiency.	YES (Streetlights Data)	YES (Street Lighting) (Energy Collection)	N/A	YES Subcon-tractor	YES (Best/ Energy Optimi-zation)	YES (Operator)
Traffic Monitoring	As a city operator I would like to reduce traffic congestion within the city by deploying cameras and edge gateways.	YES (Traffic Lights Data)	YES (Traffic Data) (Congested Roads)	N/A	YES Subcon-tractor	YES (Best Traffic Conditions)	YES (Operator and Citizen)
Environmental Monitoring	As a city operator, I would like to understand certain conditions and pollutants in the city environment. I would like the gases and particulates to be reported based on threshold events.	YES (Weather Data)	YES (Air Quality Data) (Polluted Areas)	N/A	YES Subcon-tractor	YES (Best Air Areas)	YES (Operator and Citizen)
Smart Parking	As a city operator I would like to provide the citizens with open parking space indication that is either presented by a digital sign or delivered via a mobile application.	YES (Parking Data)	YES (Parking Data) (Occupancy Spaces)	N/A	YES Subcon-tractor	YES (Available Parking Spots)	YES (Operator and Citizen)

Digital Kiosk	As a city operator, I would like to provide an element of citizen engagement via the use of digital kiosks that will deliver city information such as nearby restaurants, parking, and heat maps for where events are.	YES (City Activities Data)	YES (City Data) (Activities Agenda)	N/A	YES Subcon-tractor	YES (City Activities)	YES (Operator and Citizen)

Appendix C. Analyzing Smart City/Community Systems

This appendix provides details of the H-KPI method for representing the information relationships in a smart city/community implementation. The goal is to enable reliable analyses, including computational methods. In this method, a relationship is defined as an information flow comprising the movement of data from a source to a destination over a communication path. The set of all relationships can be represented by an ordered graph for visualizing all or selected subsets of the information flows in a smart city/community implementation.

Each relationship is represented by an ordered tuple of four components in the form (reuse$_{a\text{-}n}$; {source_type}, {path$_{\alpha}$}, {destination, processed data type → F(ID)}):

1) The set of reuse relationships (reuse$_{a\text{-}n}$). A 'use' is defined as the use of a specified data type and source to enable a defined infrastructure service or community benefit. A 'reuse' is the use of that same data for additional infrastructure services or community benefits. A 'reuse relationship' is an information flow that precedes in the directed graph the information flow specified in the tuple and is part of the path that provides the data to be reused.
2) Data source and data type (source_type). The data source is any node on the graph – including applications, platforms, or technologies such as sensors – that has data that can be accessed for use. Data type denotes the data model, taxonomy, or other specification or description for facilitating use of the data.
3) Path for information flow (path$_{\alpha}$). A path specifies the set of communications systems used to transmit data from source to destination. A path may be composed of one or more network types and associated protocols for wired and wireless communications.
4) Destination, processed data type, and input data processing (destination, processed data type → F(ID)). The destination is any node on the graph – including applications and platforms – capable of receiving data for use or further transmission. Since many destination nodes such as platforms or applications process input data through aggregation, reformatting, conversion of units, etc., this data processing is also specified in the destination element of the tuple as follows. The processed data type is the data model, taxonomy, or other specification or description of the data that has been processed at the destination and made available for use or further transmission. Processing (denoted by F) of input data (ID; i.e., data received by the destination from a source) to produce the processed data type is represented by F(ID) such that the relationship between the processed data type and the input data is represented by the expression "processed data type → F(ID)." Note that F is an identity function for a destination that does not process input data before subsequent use or transmission.

The two types of relationships are dependencies and connectors. Dependencies are information flows required for the first or original use of a specified data type and are represented by tuples in which reuse is a null set. Connectors are information flows required for additional uses of a specified data type beyond the first or original use and are represented by tuples in which reuse is a non-null set. Other than the contents of the reuse set, tuples for dependencies and connectors are of the same form.

All or a subset of the information flows in a smart city/community implementation can be visualized as a directed graph or described through a list of tuples. The graph and tuples list are just different representations of the same thing. The graph can be constructed from the tuples list and vice versa.

The graph in Figure C1 represents a hypothetical smart city/community implementation for purposes of illustration. The nodes in this graph are of three types:

1) Original sources, such as sensors, are nodes that generate data de novo. In terms of tuples, sources can be identified as those nodes that are not destinations in any of the tuples.
2) Platforms are nodes that serve to aggregate input data for further transmission and may serve as a data source for other nodes but do not directly provide an infrastructure service or community benefit. The function of platforms lies in making data readily available for use by a range of service and benefit applications.
3) Infrastructure service and community benefit nodes represent applications for infrastructure management, such as control of building HVAC systems, or for providing benefits such as information about energy savings or health and well-being.
4) The edges are represented by arrows with the direction indicating the movement of data from source to destination along the designated communications path. Dependencies are shown in black and connectors are in blue.

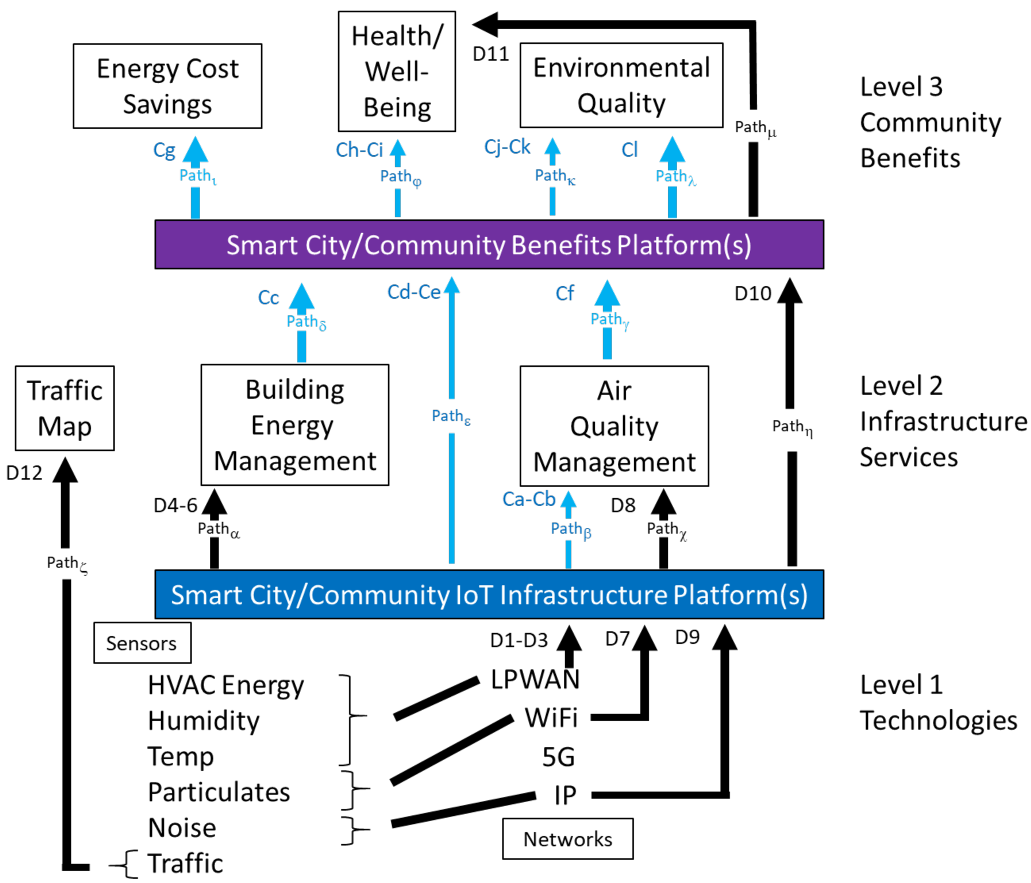

Figure C1 – Smart City Systems Graph

The complete set of tuples for the system represented in Figure C1 above is as follows:

- Dependency 1 (D1) = (nullset; {Sensor_HVAC Energy}, {LPWAN}, {IoT Platform, IoTP Energy -> F(HVAC Energy)})
- Dependency 2 (D2) = (nullset; {Sensor_Humidity}, {LPWAN}, {IoT Platform, IoTPHumidity -> F(Humidity)})
- Dependency 3 (D3) = (nullset; {Sensor_Temp}, {LPWAN}, {IoT Platform, IoTP Temp -> F(Temp)})
- Dependency 4 (D4): (nullset; {IoTPlatform_IoTP Energy}, {Pathα}, {BEM, BEM Energy -> F(IoTP Energy)})
- Dependency 5 (D5): (nullset; {IoTPlatform_IoTP Humidity}, {Pathα}, {BEM, BEM Humidity -> F(IoTP Humidity)})
- Dependency 6 (D6): (nullset; {IoTPlatform_IoTP Temp}, {Pathα}, {BEM, BEM Temp -> IoTP Temp)})
- Dependency 7 (D7) = (nullset; {Sensor_Particulates}, {WiFi}, {IoT Platform, IoTP Particulates -> F(Particulates)})
- Dependency 8 (D8) = (nullset; {IoT Platform_IoTP Particulate}, {WiFi}, {AQM, AQM Particulate -> F(IoTP Particulate)})
- Dependency 9 (D9) = (nullset; {Sensor_Noise}, {IP}, {IoT Platform, IoTP Noise -> F(Noise)})
- Dependency 10 (D10) = (nullset; {IoT Platform_IoTP Noise}, {Pathη}, {Benefits Platform, BenPP Noise -> F(IoTP Noise)})
- Dependency 11 (D11) = (nullset; {Benefits Platform_BenP Noise}, {Pathμ}, {Env Qualtiy, EQ Particulates -> F(BenP Particulates)})
- Dependency 12 (D12): (nullset; {Sensor_Traffic}, {Pathζ}, {Traffic Map, TM Traffic -> F(Traffic)})
- Connector a (Ca) = ({D2}; {IoT Platform_IoTP Humidity}, {Pathβ}, {AQM, AQM Humidity -> F(IoTP Humidity)})
- Connector b (Cb) = ({D3}; {IoT Platform_IoTP Temp}, {Pathβ}, {AQM, AQM Temp -> IoTP Temp})
- Connector c (Cc) = ({D1, D4}; {BEM_BEM Energy}, {Pathδ}, {Benefits Platform, BenP Energy F(BEM Energy)})
- Connector d (Cd) = ({D2}; {IoT Platform_IoTP Humidity}, {Pathε}, {Benefits Platform, BenP Humidity -> F(IoTP Humidity)})
- Connector e (Ce) = ({D3}; {IoT Platform_IoTP Temp}, {Pathε}, {Benefits Platform, BenP Temp -> F(IoTP Temp)})
- Connector f (Cf) = ({D9, D10}; {AQM_AQM Particulates}, {Pathγ}, {Benefits Platform, BenP Particulates -> F(AQM Particulates)})
- Connector g (Cg) = ({Cc}; {Benefits Platform_BenP Energy}, {Pathι}, {Energy Cost Savings, ECS Energy -> F(BenP Energy)})
- Connector h (Ch) = ({Cd}; {Benefits Platform_BenP Humidity}, {Pathκ}, {Env Quality, EQ Humidity -> F(BenP Humidity)})
- Connector i (Ci) = ({Ce}; {Benefits Platform_BenP Temp}, {Pathκ}, {Env Quality, EQ Temp -> F(BenP Temp)})
- Connector j (Cj) = ({Cd}; {Benefits Platform_BenP Humidity}, {Pathκ}, {Env Quality, EQ Humidity -> F(BenP Humidity)})
- Connector k (Ck) = ({Ce}; {Benefits Platform_BenP Temp}, {Pathκ}, {Env Quality, EQ Temp -> F(BenP Temp)})
- Connector l (Cl) = ({Cf}; {Benefits Platform_BenP Particulates}, {Pathλ}, {Env Quality, EQ Particulates -> F(BenP Particulates)})

Note that ordering within tuples with multiple groups of unlinked connectors and dependencies is by increasing cardinality for their sets of reuses and sources, respectively. The following sections illustrate stepwise assembly of the graph and examples of operations on tuples.

Step 1: Traffic Map Information Flow

Information flow to the Traffic Map infrastructure service is a single, dedicated relationship:

- Dependency 12 (D12): (nullset; {Sensor_Traffic}, {Pathζ}, {Traffic Map, TM Traffic -> F(Traffic)})

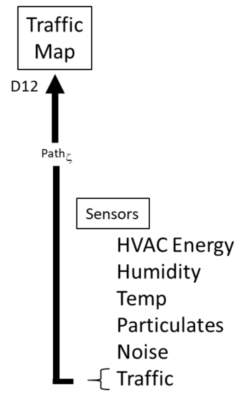

Figure C2 – Traffic Map

Step 2: IoT Infrastructure Platform Information Flow

Information flow to the IoT Platform is a composition of these relationships:

- Dependency 1 (D1) = (nullset; {Sensor_HVAC Energy}, {LPWAN}, {IoT Platform, IoTP Energy -> F(HVAC Energy)})
- Dependency 2 (D2) = (nullset; {Sensor_Humidity}, {LPWAN}, {IoT Platform, IoTPHumidity -> F(Humidity)})
- Dependency 3 (D3) = (nullset; {Sensor_Temp}, {LPWAN}, {IoT Platform, IoTP Temp -> F(Temp)})
- Dependency 7 (D7) = (nullset; {Sensor_Particulates}, {WiFi}, {IoT Platform, IoTP Particulates -> F(Particulates)})
- Dependency 9 (D9) = (nullset; {Sensor_Noise}, {IP}, {IoT Platform, IoTP Noise -> F(Noise)})

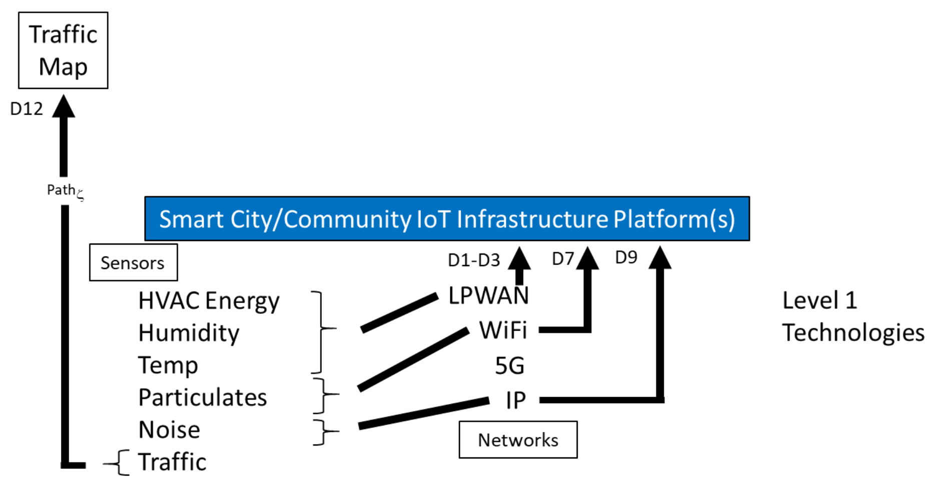

Figure C3 – Infrastructure Services Platform

Step 3: Building Energy Management (BEM) Information Flow

Information flow to the Building Energy Management (BEM) service is a composition of these relationships:

- Dependency 4 (D4): (nullset; {IoTPlatform_IoTP Energy}, {Pathα}, {BEM, BEM Energy -> F(IoTP Energy)})
- Dependency 5 (D5): (nullset; {IoTPlatform_IoTP Humidity}, {Pathα}, {BEM, BEM Humidity -> F(IoTP Humidity)})
- Dependency 6 (D6): (nullset; {IoTPlatform_IoTP Temp}, {Pathα}, {BEM, BEM Temp -> IoTP Temp)})

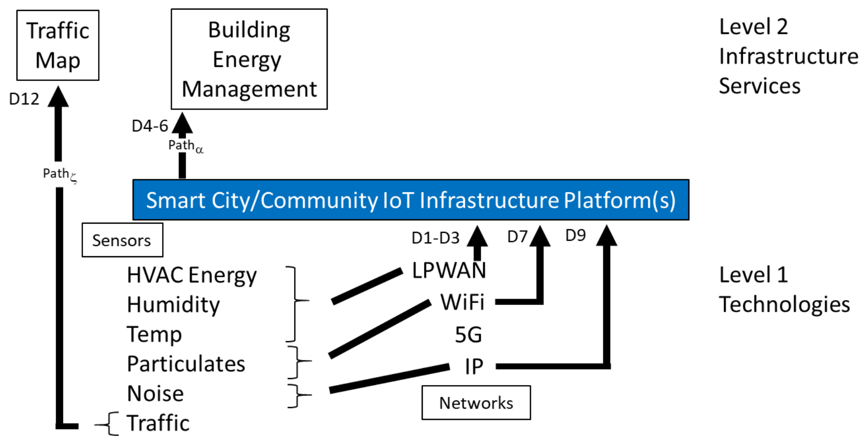

Figure C4 – Building Energy Management

Step 4: Air Quality Management Information Flow

Information flow to the Air Quality Mgt. (AQM) service is a composition of these relationships:

- Connector a (Ca) = ({D2}; {IoT Platform_IoTP Humidity}, {Pathβ}, {AQM, AQM Humidity -> F(IoTP Humidity)})
- Connector b (Cb) = ({D3}; {IoT Platform_IoTP Temp}, {Pathβ}, {AQM, AQM Temp -> IoTP Temp})
- Dependency 8 (D8) = (nullset; {IoT Platform_IoTP Particulate}, {WiFi}, {AQM, AQM Particulate -> F(IoTP Particulate)})

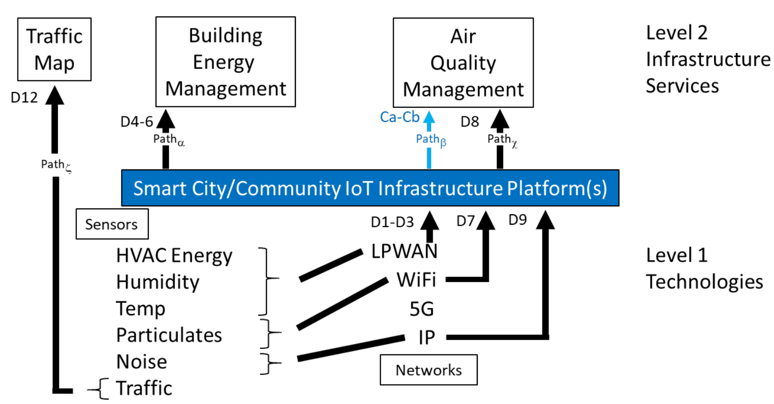

Figure C5 – Air Quality Management

Step 5: Community Benefits Platform Information Flow

Information flow to the Benefits Platform (BenP) is a composition of these relationships:

- Connector c (Cc) = ({D1, D4}; {BEM_BEM Energy}, {Pathδ}, {Benefits Platform, BenP Energy F(BEM Energy)})
- Connector d (Cd) = ({D2}; {IoT Platform_IoTP Humidity}, {Pathε}, {Benefits Platform, BenP Humidity -> F(IoTP Humidity)})
- Connector e (Ce) = ({D3}; {IoT Platform_IoTP Temp}, {Pathε}, {Benefits Platform, BenP Temp -> F(IoTP Temp)})
- Connector f (Cf) = ({D9, D10}; {AQM_AQM Particulates}, {Pathγ}, {Benefits Platform, BenP Particulates -> F(AQM Particulates)})
- Dependency 10 (D10) = (nullset; {IoT Platform_IoTP Noise}, {Pathη}, {Benefits Platform, BenPP Noise -> F(IoTP Noise)})

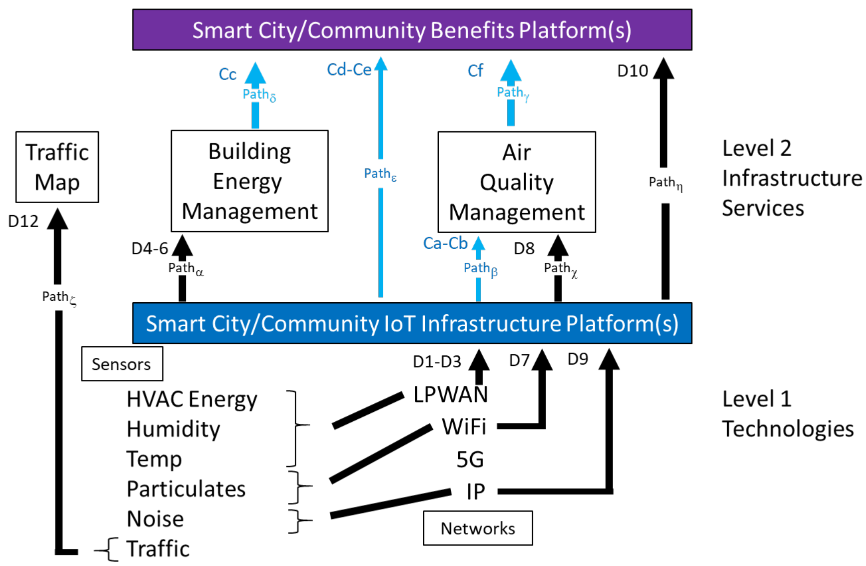

Figure C6 – Community Benefits Platform

Step 6: Environmental Quality Information Flow

Information flow to the Environmental Quality (EQ) application/benefit is a composition of Humidity, Temp and Particulates data through these relationships :

- Connector j (Cj) = ({Cd}; {Benefits Platform_BenP Humidity}, {Pathκ}, {Env Quality, EQ Humidity -> F(BenP Humidity)})
- Connector k (Ck) = ({Ce}; {Benefits Platform_BenP Temp}, {Pathκ}, {Env Quality, EQ Temp -> F(BenP Temp)})
- Connector l (Cl) = ({Cf}; {Benefits Platform_BenP Particulates}, {Pathλ}, {Env Quality, EQ Particulates -> F(BenP Particulates)})

Figure C7 below shows the addition of the Environmental Quality application to the overall graph.

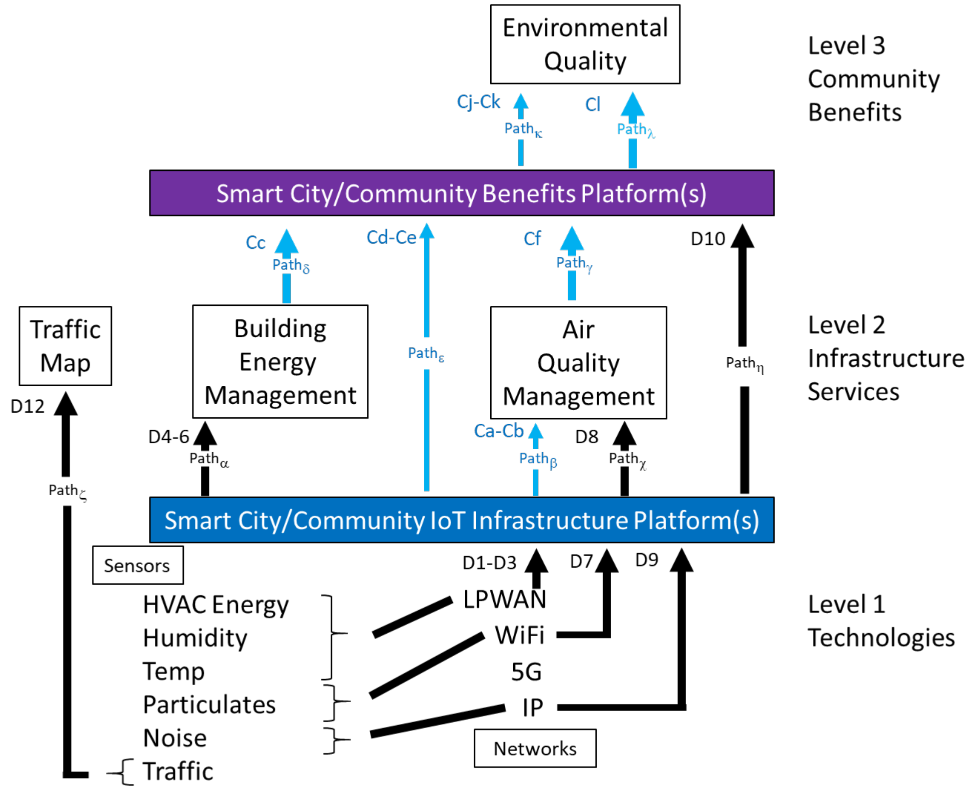

Figure C7 – Environmental Quality

Step 7: Health and Well-Being Information Flow

Information flow to the Health/Well-Being (HWB) application/benefit is a composition of humidity, temp, particulate, and noise data flowing through these paths:

- Connector j (Cj) = ({Cd}; {Benefits Platform_BenP Humidity}, {Pathκ}, {Env Quality, EQ Humidity -> F(BenP Humidity)})
- Connector k (Ck) = ({Ce}; {Benefits Platform_BenP Temp}, {Pathκ}, {Env Quality, EQ Temp -> F(BenP Temp)})
- Connector l (Cl) = ({Cf}; {Benefits Platform_BenP Particulates}, {Pathκ}, {Env Quality, EQ Particulates -> F(BenP Particulates)})
- Dependency 11 (D11) = (nullset; {Benefits Platform_BenP Noise}, {Pathμ}, {Env Quality, EQ Noise-> F(BenP Noise)})

Figure C8 below shows the addition of the Health and Well-Being application to the overall graph.

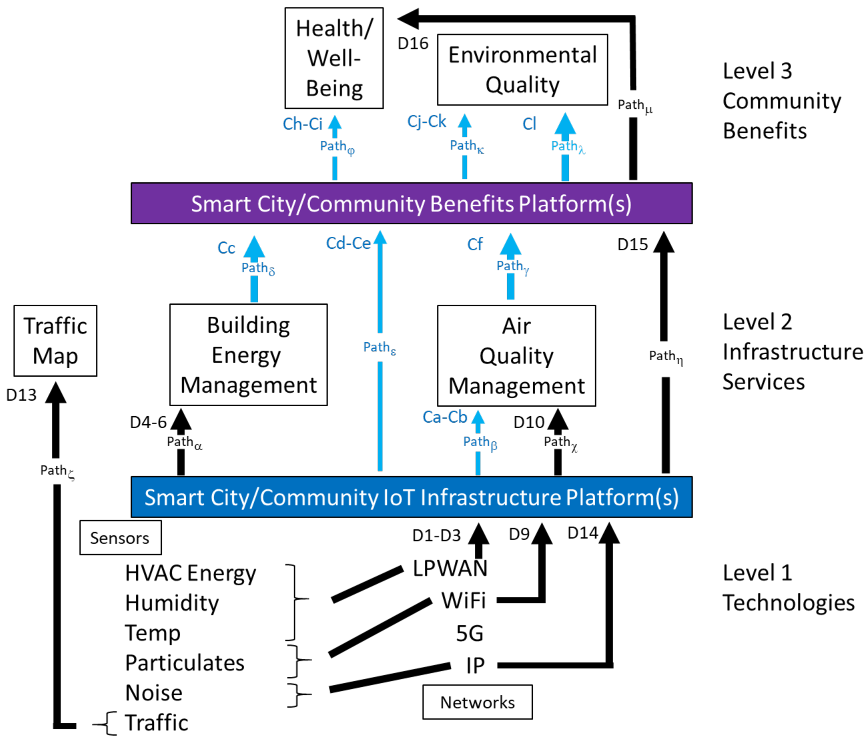

Figure C8 – Health and Well-Being

Operations on Sets of Relationship Tuples

Example 1: A hypothetical design phase question is: What would it take to add an Energy Cost Savings Dashboard Application as a community benefit to the system shown in Fig. C8 above? To determine the answer, a search could be undertaken across the set of all tuples for sources and destinations that include 'Energy.' The results of that search are shown in the list below with energy data types highlighted in red. The corresponding nodes are indicated with large red arrows in the graph in Fig. C9 below.

- Dependency 4 (D4): (nullset; {IoTPlatform_IoTP Energy}, {Pathα}, {BEM, BEM Energy -> F(IoTP Energy)})
- Dependency 1 (D1) = (nullset; {Sensor_HVAC Energy}, {LPWAN}, {IoT Platform, IoTP Energy -> F(HVAC Energy)})
- Connector c (Cc) = ({D1, D4}; {BEM_BEM Energy}, {Pathδ}, {Benefits Platform, BenP Energy -> F(BEM Energy)})

Any of these data types and sources could be used to construct the proposed cost savings dashboard, but the Benefits Platform and the corresponding energy data type (BenP Energy) were used to create Connector g:

- Connector g (Cg) = ({Cc}; {Benefits Platform_BenP Energy}, {Pathι}, {Energy Cost Savings, ECS Energy -> F(BenP Energy)})

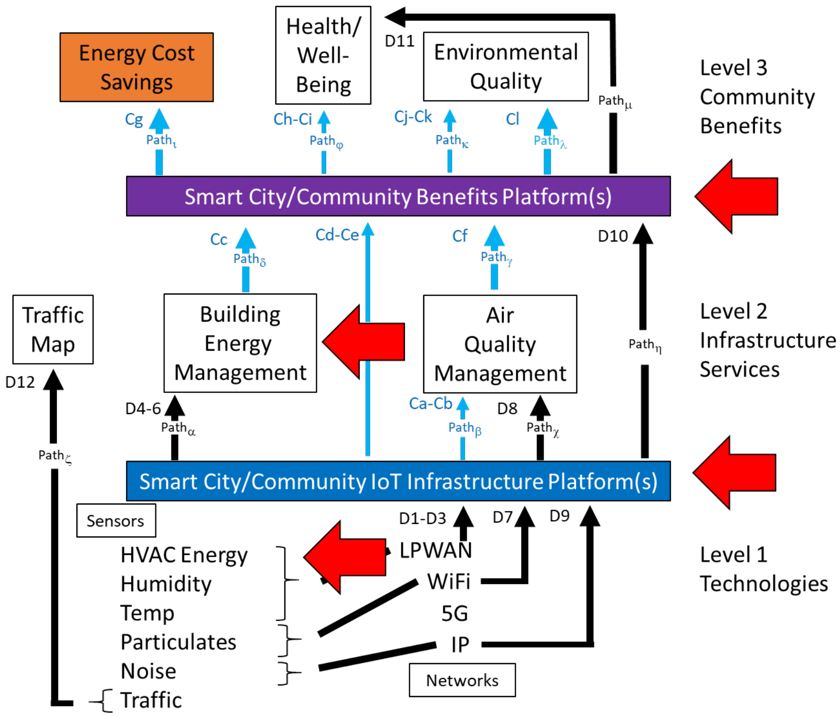

Figure C9 – Energy Cost Savings

Example 2: A second example of an operation on the set of tuples is fault tracing. Consider the hypothetical cause of a failure of the Health and Well-Being application to receive humidity data. A first step in identifying the source of the fault is to trace the path and root source of the humidity data. This can be done using a recursive search algorithm as follows.

- 1st search terms: X= HWB Y=HWB Humidity
  - Result: Connector j (Cf) = ({D2}; {Benefits Platform_BenP Humidity}, {Pathβ}, {HWB, HWB Humidity -> BenP Humidity})
- 2nd search terms: X= Benefits Platform Y=BenP Humidity
  - Result: Connector d (Cd) = ({D2}; {IoT Platform_IoTP Humidity}, {Pathε}, {Benefits Platform, BenP Humidity -> F(IoTP Humidity)})
- 3rd search terms: X= IoT Platform Y=IoTP Humidity
  - Result: Dependency 2 (D2) = (nullset; {Sensor_Humidity}, {LPWAN}, {IoT Platform, IoTPHumidity -> F(Humidity)})
- 4th search terms: X= Sensor Y=Humidity ➡ Null result identifies root source

The results of the search – the path and root source of the humidity data – are shown graphically in Fig. C10 below. Note that both the search and the construction of the graphical representation of search results are amenable to computational methods.

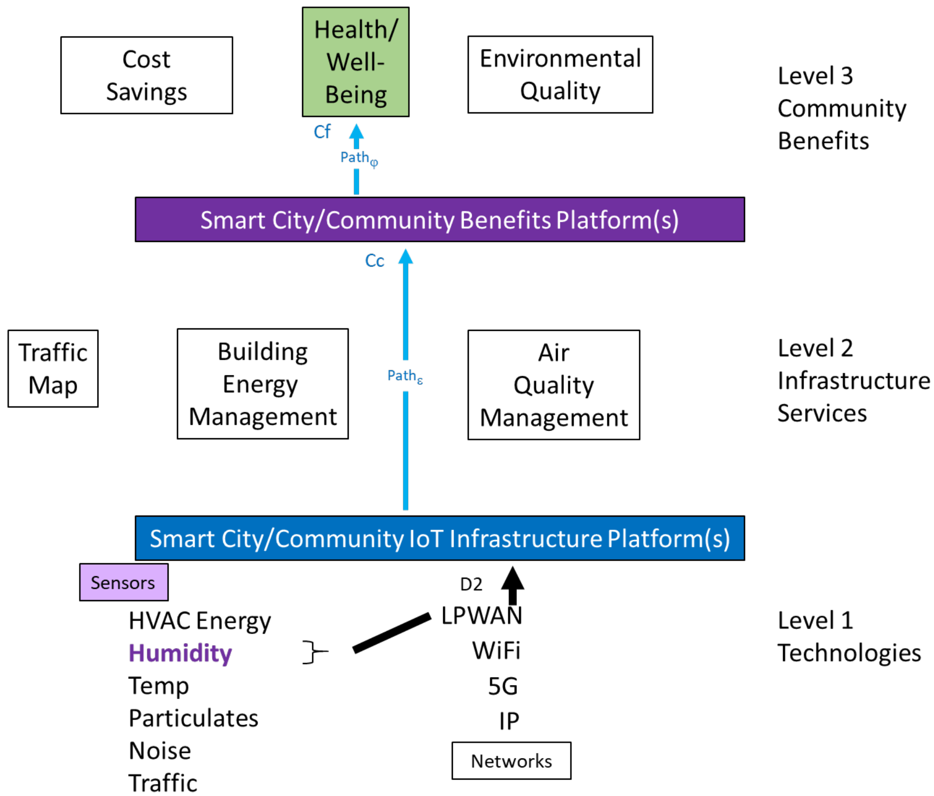

Figure C10 – Humidity Data Path and Source

Appendix D. Methods for Measuring 'Smart'

This appendix provides details of the H-KPI methodology for measuring 'smart' for a smart city/community implementation. Here, smart is defined as the efficient use of digital technologies to provide prioritized infrastructure services and community benefits. 'Elements' are defined as the relevant components of a smart/city/community implementation under review and may be districts or neighborhoods within a community, departments within a city government, communities within a region, etc.

The five metrics for this measurement are as follows:

1. alignment of community priorities across elements;
2. investment alignment with community priorities;
3. investment efficiency;
4. information flow density; and
5. quality of infrastructure services and community benefits.

The following sections set out H-KPI measurement concepts for each of these metrics. Measurements for each of these metrics are carried out for each KPI in each element, producing a table of results. These tables and associated calculations are presented for each metric below, followed by definitions of the calculations.

Metric 1: Alignment of Community Priorities Across Elements

	Element 1	Element 2	Element 3	Element 4	Element 5	Element 6	Element_n	Priority Factor Roll-up (PFR_i)	Target Priority Factors (TPF_i)	Priority Factor Alignment (PFA_i)
KPI 1	PF_{11}	PF_{12}	PF_{13}	PF_{14}	PF_{15}	PF_{16}	PF_{1n}	$\sum_{j=1}^{n} PF_{1j} \big/ n$	TPF_1	$\lvert TPF_1 - PFR_1 \rvert$
KPI 2	"	"	"	"	"	"	"		"	"
KPI 3	"	"	"	"	"	"	"	"	"	"
KPI 4	"	"	"	"	"	"	"	"	"	"
KPI 5	"	"	"	"	"	"	"	"	"	"
KPI 6	"	"	"	"	"	"	"		"	"
KPI_m	PF_{m1}	PF_{m2}	PF_{m3}	PF_{m4}	PF_{m5}	PF_{m6}	PF_{mn}	$\sum_{j=1}^{n} PF_{mj} \big/ n$	TPF_m	$\lvert TPF_m - PFR_m \rvert$
Sum	1	1	1	1	1	1	1	1	1	PFA = $\sum_{i=1}^{m} PFA_i \big/ m$

- Priority Factor_{ij} (PF_{ij}) is the assigned fractional priority for KPI_i in Element_j where *i* varies from 1 to m and *j* varies from 1 to n and where the sum of all Priority Factors for Element_j is one.

$$\sum_{i=1}^{m} PF_{ij} = 1 \qquad (1)$$

- The Priority Factor Roll-up_i (PFR_i) is the fraction of all Priority Factors assigned to KPI_i across all Elements(*j*)

$$PFR_i = \frac{\sum_{j=1}^{n} PF_{ij}}{\sum_{i=1}^{m} \sum_{j=1}^{n} PF_{ij}} = \frac{\sum_{j=1}^{n} PF_{ij}}{n} \qquad (2)$$

- The Target Priority Factor_i (TPF_i) is the fractional priority assigned to KPI_i at a higher level of authority or composition. An example would be priority targets set city-wide rather than by individual districts.

$$\sum_{i=1}^{m} TPF_i = 1 \tag{3}$$

- The Priority Factor Alignment relative to KPI_i (PFA_i) is the distance between TPF_i and PFR_i and is an indicator of how closely element-level priorities collectively meet guidance.

$$PFA_i = |TPF_i - PFR_i| \tag{4}$$

- The overall Priority Factor Alignment Index (P) is the mean of the Priority Factor Alignment values for all KPIs across all elements.

$$P = \sum_{i=1}^{m} PFA_i \Big/ m \tag{5}$$

Metric 2: Investment Alignment with Community Priorities

	Element 1	Element 2	Element 3	Element 4	Element 5	Element 6	Element_n	Mean Alignment Factor ($\overline{IF}_i$)
KPI 1	IAF_{11}	IAF_{12}	IAF_{13}	IAF_{14}	IAF_{15}	AIF_{16}	IAF_{1n}	$\overline{IAF}_1 = \sum_{j=1}^{n} IAF_{1j} \Big/ n$
KPI 2	"	"	"	"	"	"	"	
KPI 3	"	"	"	"	"	"	"	"
KPI 4	"	"	"	"	"	"	"	"
KPI 5	"	"	"	"	"	"	"	"
KPI 6	"	"	"	"	"	"	"	
KPI_m	IAF_{m1}	IAF_{m2}	IAF_{m3}	IAF_{m4}	IAF_{m5}	IAF_{m6}	IAF_{mn}	$\overline{IAF}_m = \sum_{j=1}^{n} IAF_{mj} \Big/ n$
								$IA = \sum_{i=1}^{m} \overline{IAF}_i \Big/ m$

- Investment Alignment Factor (IAF_{ij}) for KPI_i in Element_j

$$IAF_{ij} = 1 - |PF_{ij} - ID_{ij}| \tag{6}$$

- Mean Investment Alignment Factor ($\overline{IAF}_i$) for KPI_i across all elements (*j*):

$$\overline{IAF}_i = \sum_{j=1}^{n} IAF_{ij} \Big/ n \tag{7}$$

- Mean Overall Investment Alignment Index (IA) for all KPIs across all elements:

$$IA = \sum_{i=1}^{m} \overline{IAF}_i \Big/ m \tag{8}$$

Metric 3: Investment Efficiency Factor

	Element 1	Element 2	Element 3	Element 4	Element 5	Element 6	Element$_n$	Mean Efficiency Factor ($\overline{\text{EF}}_i$)
KPI 1	IEF_{11}	IEF_{12}	IEF_{13}	IEF_{14}	IEF_{15}	IEF_{16}	IEF_{1n}	$\overline{\text{IEF}}_1 = \sum_{j=1}^{n} \text{IEF}_{1j} / n$
KPI 2	"	"	"	"	"	"	"	
KPI 3	"	"	"	"	"	"	"	"
KPI 4	"	"	"	"	"	"	"	"
KPI 5	"	"	"	"	"	"	"	"
KPI 6	"	"	"	"	"	"	"	$\overline{\text{IEF}}_m = \sum_{j=1}^{n} \text{IEF}_{mj} / n$
KPI$_m$	IEF_{m1}	IEF_{m2}	IEF_{m3}	IEF_{m4}	IEF_{m5}	IEF_{m6}	IEF_{mn}	
								$E = \sum_{i=1}^{m} \overline{\text{IEF}}_i / m$

- Investment Efficiency Factor (IEF_{ij}) for KPI_{ij} (where Investment $_{ij} \neq 0$):

$$\text{IEF}_{ij} = \frac{\#Dependencies_{ij} + \#Connectors_{ij}}{Investment_{ij}} \tag{9}$$

- Mean Investment Efficiency Factor ($\overline{\text{IEF}}_i$) for KPI_i across all elements (j):

$$\overline{\text{IEF}}_i = \sum_{j=1}^{n} \text{IEF}_{ij} \Big/ n \tag{10}$$

- Mean Overall Investment Efficiency Index (E) for all KPIs across all elements:

$$E = \sum_{i=1}^{m} \overline{\text{IEF}}_i \Big/ m \tag{11}$$

Metric 4: Information Flow Density

	Element 1	Element 2	Element 3	Element 4	Element 5	Element 6	Element_n	Mean Data Factor ($\overline{DF}_i$)
KPI 1	ID_{11}	ID_{12}	ID_{13}	ID_{14}	ID_{15}	ID_{16}	ID_{1n}	$\overline{ID}_1 = \left\lvert \bigcup_{j=1}^{n} (R_{1j}) \right\rvert \Big/ n$
KPI 2	"	"	"	"	"	"	"	
KPI 3	"	"	"	"	"	"	"	"
KPI 4	"	"	"	"	"	"	"	"
KPI 5	"	"	"	"	"	"	"	"
KPI 6	"	"	"	"	"	"	"	
KPI_m	ID_{m1}	ID_{m2}	ID_{m3}	ID_{m4}	ID_{m5}	ID_{m6}	ID_{mn}	$\overline{ID}_m = \left\lvert \bigcup_{j=1}^{n} (R_{mj}) \right\rvert \Big/ n$
							DI =	$\left\lvert \bigcup_{i=1}^{m} \bigcup_{j=1}^{n} (R_{ij}) \right\rvert \Big/ (m \times n)$

- Information Flow Density Factor (ID_{ij})

$$(ID_{ij}) = \frac{Information\ Flows_{ij}}{Selected\ Density\ Factor} \tag{12}$$

Examples of units are info flow per capita or per sq mile, etc.

Where

Information Flows$_{ij}$ is the total number of items in the set of supporting *Relationships* (R_{ij}) for KPI_i in $Element_j$

$$Information\ Flows_{ij} = |R_{ij}| \tag{13}$$

The set of supporting *Relationships*$_{ij}$ is the union of the sets of *Dependencies* (D_{ij}) and *Connectors* (C_{ij}) supporting the infrastructure services and/or community benefits for KPI_i in $Element_j$.

$$(R_{ij}) = (D_{ij}) \cup (C_{ij}) \tag{14}$$

Selected Density Factor is the selected smart city comparator such as population, geographic area, GDP, etc., for comparisons across cities, communities, districts, departments, neighborhoods, etc.

- Mean Density Factor ($\overline{ID}_i$) for KPI_i across all elements (j):

$$\overline{ID}_i = \left\lvert \bigcup_{j=1}^{n} (R_{ij}) \right\rvert \Big/ n \tag{15}$$

- Information Flow Density Index (DI) for all KPIs across all elements:

$$DI = \left\lvert \bigcup_{i=1}^{m} \bigcup_{j=1}^{n} (R_{ij}) \right\rvert \Big/ (m \times n) \tag{16}$$

Metric 5: Quality Factor

	Element 1	Element 2	Element 3	Element 4	Element 5	Element 6	Element$_n$	Mean Quality Factor ($\overline{QF}_i$)
KPI 1	QF_{11}	QF_{12}	QF_{13}	QF_{14}	QF_{15}	QF_{16}	QF_{1n}	$\sum_{j=1}^{n} QF_{ij} / n$
KPI 2	"	"	"	"	"	"	"	
KPI 3	"	"	"	"	"	"	"	"
KPI 4	"	"	"	"	"	"	"	"
KPI 5	"	"	"	"	"	"	"	"
KPI 6	"	"	"	"	"	"	"	
KPI$_m$	QF_{m1}	QF_{m2}	QF_{m3}	QF_{m4}	QF_{m5}	QF_{m6}	QF_{mn}	$\sum_{j=1}^{n} QF_{mj} / n$
								$Q = \sum_{i=1}^{m} \overline{QF}_i / m$

- Quality factor (QF_{ij}) for KPI_i in $element_j$ (example using the six sigma method):

$$QF_{ij} = \frac{(\text{KPI Spec}_{ij} - \text{Mean}_{ij})}{\sigma_{ij}} \tag{17}$$

Where

$(X_a \ldots X_b)$ = set of measurements for KPI_{ij} (18)

KPI Spec_{ij} = Target specification for KPI_i in $Element_j$ (19)

$$\text{Mean } (\bar{x}) = \frac{\sum x}{n} \tag{20}$$

$$\sigma_{ij} = \sqrt{\frac{(x_i - \bar{x})^2}{n-1}} \tag{21}$$

- Mean Quality Factor ($\overline{QF}_i$) for KPI_i across all elements:

$$\overline{QF}_i = \sum_{j=1}^{n} QF_{ij} / n \tag{22}$$

- Mean Overall Quality Index (Q) for all KPIs across all elements:

$$Q = \sum_{i=1}^{m} \overline{QF}_i / m \tag{23}$$

Appendix E. Analytical Methods

Statistical Methods

This section briefly reviews three methods commonly used to perform statistical analyses over collected data and describes their advantages and disadvantages for use in the H-KPIs Framework.

The Raking Statistical Method

As described in [20], the raking method is an iterative proportional fitting statistical method. Raking defines a set of variables where the total or global distribution of the population relative to those variables is known. Raking is an iterative method that balances the weighting for each case so that the ratios for the weighted data sample match the actual global population. The process is iterative; if the adjustment pushes other data sets out of alignment with those ratios, then the weights are adjusted again so that overall adjustments fit the desired proportion. The Raking process is repeated until the weighted distribution of all of the variables matches their specified or targeted data sets.

This method is widely used in statistical analysis, particularly in surveys where the interviewed participants can be identified, categorized, and balanced even though they may not represent the actual population distribution. In the context of smart cities, if the KPIs total number or relationships are not well-balanced but the conditions of a city are well-identified, the KPI relationships total population can be adjusted to compensate for those variations using the balancing process of the raking method.

Figure E1 illustrates the raking method, showing what happens when the number of H-KPIs in particular targeted categories do not correspond to the expected population distribution. The graphic represents the different categories of KPIs (based on color on the left-hand side of the figure) and the result of weighting using the raking method (on the right-hand side of the figure). The raking method has the potential for use in H-KPI methodology to analyze various characteristics of a smart city while using a selected subset of KPIs from the total city KPIs collection. The raking method allows assigning percentage values to the H-KPIs according to the relevance of data, which are identified and clustered by domain as shown on the right-hand side of the figure using different colors and different sizes for representing the percentages. Because the results are not necessarily aligned with the distributions between KPI categories, the collected information must be weighted to make the raking method work correctly.

Despite these advantages, a significant limitation in this method is the requirement that the variables related to the distribution of the population and their associated KPIs must be known. The dynamic organizational characteristics of cities limit the possibility of knowing the exact distribution of the relevant population, making it difficult to use the raking method.

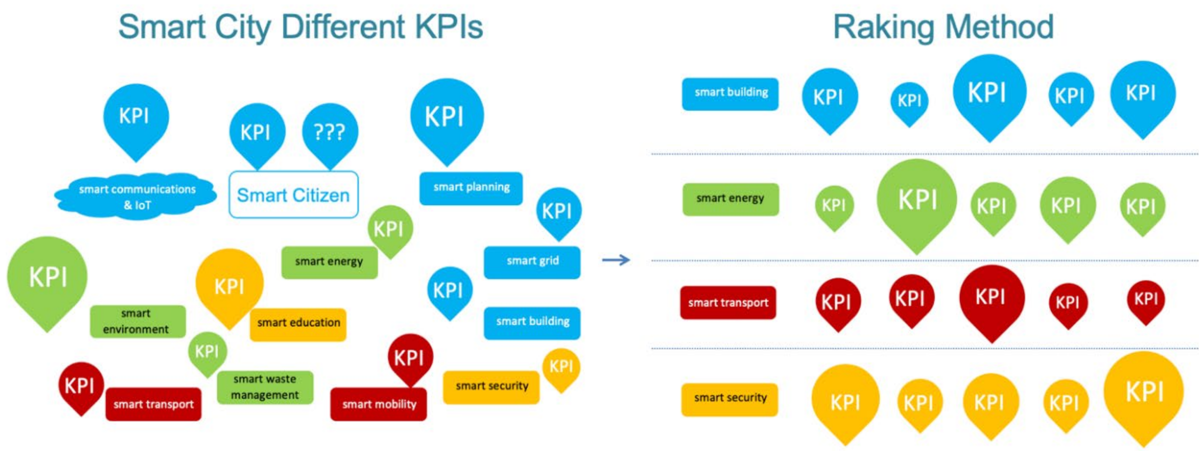

Figure E1 – Raking Statistical method

The Matching Statistical Method

Matching is another technique that has been proposed for adjusting through weighting online opt-in data samples [20]. Matching works with data samples that are representative of the population and contain all of the variables to be used in the adjustment. This method may be applied as an approach to H-KPIs measurement, with the limitation that data samples that are representative of the population need to be available and provided. This may be feasible when the analysis is done internally or when the relevant data sets are openly available. However, restrictions in data access and use can make this method impractical.

An advantage of the matching method is that its structure and model are aligned with the use of machine learning techniques as illustrated in Fig. E2. However, as mentioned above, if the KPIs of the city are not accessible, this method may not be applicable as it is necessary to know the purpose or target of the KPIs for the city system.

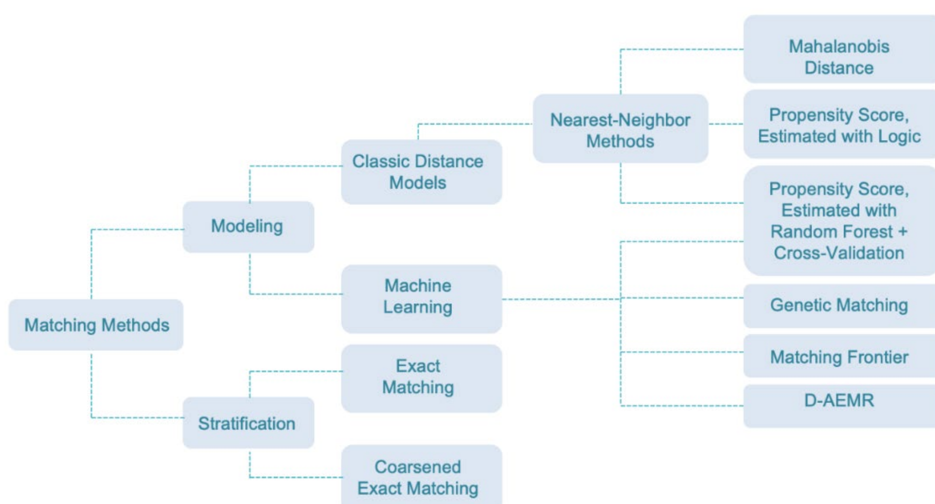

Figure E2 – Matching Statistical Method

The Propensity Weighting Statistical Method

Propensity weighting methods are used to remove the effects of observable confounders (i.e., the supposition of pre-defined variables, as in the matching method) when estimating the impact of the actions of a city on a desired outcome [20]. Propensity weighting corrects for different probabilities by weighting each case using the inverse of its probability (inverse probability weighting; IP [21]). This removes bias that might result from having different kinds of populations represented in the wrong proportions in the data samples.

Figure E3 illustrates the effects of using a propensity weighting model over a population where imbalances exist in the data samples, but they are not necessarily known. There are no pre-defined variables, but variation in the population is compensated for with the inverse probability factor. Because of its advantages and the limitations in both the raking and matching methods, the propensity weighting method is the one that the H-KPIs Framework uses to design and propose a solution for H-KPIs measurement.

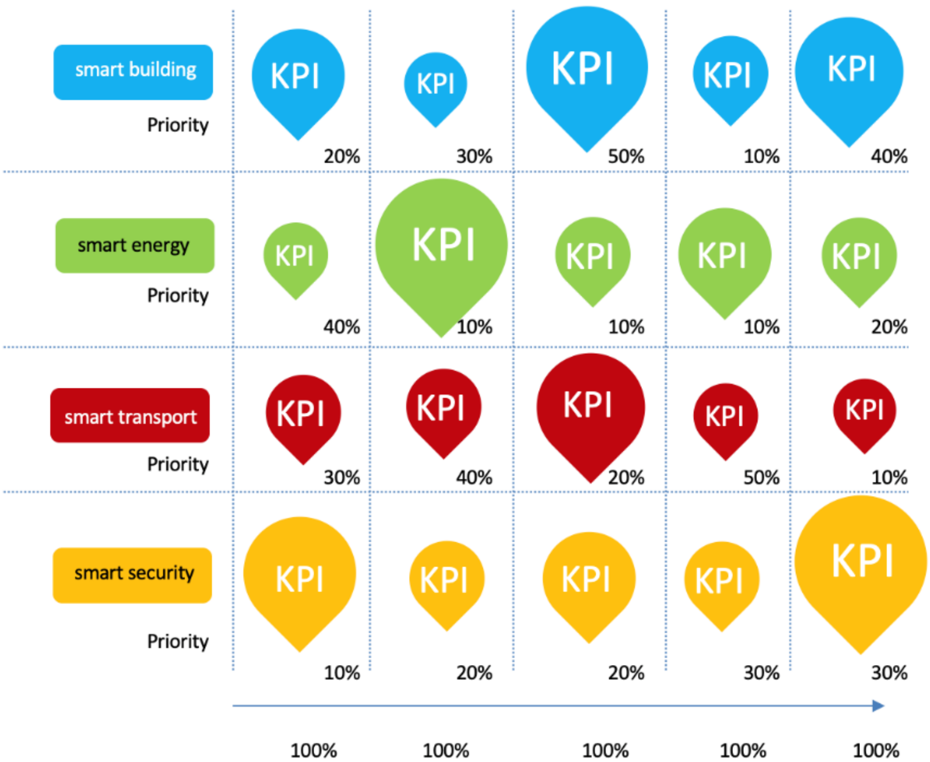

Figure E3 – Propensity Weighting Statistical Method

Group Theory

Group Theory, a topic in algebra, provides a formalism for performing calculations on abstract objects and operations. This formalism can be used for calculations on defined and abstract smart city data relationships. A group comprises a set and one or more operations on the elements of that set. Group operations are equipped with axioms that assert basic truths about those operations, e.g., commutativity and associativity. Using the definition of a group in Group Theory, a group of relationships is defined here as the set of relationships that satisfy smart city axioms asserted as "positive impact in the society" and apply these to the data from smart cities.

When this approach is applied to smart city data and the use of smart city technologies, data and data sources, services, and KPIs of a city, one of the goals is to devise functions that assess progress toward city goals and the maturity of the city with respect to its chosen KPIs. A group is formalized as a triple G=(G,*,e), where G is the set of elements of G, * represents the group operation, and e represents the identity element with respect to *.

As an indication of the defined relationships for grouping the KPIs, an instance of the use of group theory in the H-KPIs methodology is described below for indicators that share common characteristics as the set of elements of a group. This group can be used to quantify and define calculations related to KPIs, i.e., to reason quantitatively.

A G set of a city that includes its KPIs and their quantification – together with a notion of composition * based on weightings of those KPIs that make the estimate of benefit to residents, agnostic to such things as specifics of technologies and data formats – can be used to derive a numerical result. This numerical result can then be used as a self-assessment indicator of the city conditions or to measure city maturity or the performance with respect to its KPIs holistically. This mathematical approach provides a means to study ways of composing KPIs and reach precise definitions of functions used to measure KPIs holistically, i.e., H-KPIs measuring functions.