Journal of Infrastructure, Policy and Development 2024, 8(14), 8126.
https://doi.org/10.24294/jipd8126

Article

Optimization of cyber-physical urban mobility systems in developing countries: A dependency structure matrix approach with advanced artificial intelligence techniques

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CITATION

Samalna DA, Nwokam VR, Ngossaha JM, et al. (2024). Optimization of cyber-physical urban mobility systems in developing countries: A dependency structure matrix approach with advanced artificial intelligence techniques. Journal of Infrastructure, Policy and Development. 8(14): 8126. https://doi.org/10.24294/jipd8126

ARTICLE INFO

Received: 22 July 2024
Accepted: 22 October 2024
Available online: 20 November 2024

Abstract: Cyber-physical Systems (CPS) have revolutionized urban transportation worldwide, but their implementation in developing countries faces significant challenges, including infrastructure modernization, resource constraints, and varying internet accessibility. This paper proposes a methodological framework for optimizing the implementation of Cyber-Physical Urban Mobility Systems (CPUMS) tailored to improve the quality of life in developing countries. Central to this framework is the Dependency Structure Matrix (DSM) approach, augmented with advanced artificial intelligence techniques. The DSM facilitates the visualization and integration of CPUMS components, while statistical and multivariate analysis tool such as Principal Component Analysis (PCA) and artificial intelligence methods such as K-means clustering enhance complex system the analysis and optimization of complex system decisions. These techniques enable engineers and urban planners to design modular and integrated CPUMS components that are crucial for efficient, and sustainable urban mobility solutions. The interdisciplinary approach addresses local challenges and streamlines the design process, fostering economic development and technological innovation. Using DSM and advanced artificial intelligence, this research aims to optimize CPS-based urban mobility solutions, by identifying critical outliers for targeted management and system optimization.

Keywords: Cyber-Physical Systems; urban mobility; multilevel analysis; dependency structure matrix; artificial intelligence; developing countries

1. Introduction

The integration of Cyber-Physical Systems (CPS) technology in urban environments has facilitated the development of smart cities and intelligent transportation systems, promising efficient, sustainable, and interconnected mobility networks (Chakraborty and He, 2020). However, the inherent complexity of CPS, characterized by the intricate convergence of multi-physical systems and complex interactions, poses significant challenges to the effective implementation of these advanced solutions (Samalna et al., 2023a).

Developing countries face unique mobility challenges due to rapid urbanization, population growth, limited resources, uneven internet access, and the need for increased awareness and education, as well as a deep understanding of local challenges, cultures, and existing practices (Balsalobre et al., 2023; Metaxas et al., 2023; Ngossaha et al., 2024). Wegener (2013) highlights the urgent need to renovate urban mobility in these countries, and provides an overview of the drivers, feedback mechanisms, and constraints of mobility in relation to depleting energy resources. Similarly, Hunjra et al. (2024) suggest that developing countries should benefit from sustainable projects, and propose a tool to assess the sustainability of urban transport projects based on the integration of indigenous and scientific knowledge.

Demissie et al. (2016) argue that integrating Information and Communication Technology (ICT) tools into mobility systems has the potential to meet the diverse needs of city urban dwellers in developing countries. To address these challenges, it is crucial to develop urban mobility systems that are not only technologically advanced, but also flexible, modular, and sustainable. This requires a comprehensive and systematic approach that takes into account the various factors that influence the implementation of CPS in these contexts.

The integration of Cyber-Physical Systems (CPS) into urban mobility systems offers flexible and sustainable solutions to meet today’s challenges (Juma and Shaalan, 2020). However, the implementation of tightly coupled CPS into a complex system of interconnected components with interactive dependencies poses significant challenges. Engineering methods can help overcome these challenges by providing a systematic approach to designing and optimizing complex systems, and understanding their dependencies and behavioral characteristics (Wilson and Vasile, 2023). In this context, this paper aims to explore an optimized approach for the implementation of CPS-based Urban Mobility Systems (CPUMS) in developing countries. The core of this approach is the use of the Dependency Structure Matrix (DSM), a powerful system engineering tool that enables the identification of critical dependencies and key factors essential for successful CPS integration. By organizing interactions within the system, the DSM provides valuable insight into the intricate relationships between system components, facilitating effective decision-making and resource allocation.

In addition, to improve the implementation process, we use advanced dimensionality reduction techniques such as Principal Component Analysis (PCA) and the K-means clustering algorithm with the Calinski-Harabasz index. These methods play an important role in identifying the optimal number of clusters and streamlining the clustering process, thereby facilitating a deeper understanding of CPUMS development.

The rest of this paper is structured as follows. Section 2 reviews the related works on CPUMS and design and requirement engineering approaches for modeling complex system. Section 3 presents our methodological approach for designing a flexible system architecture, including our proposed approach and system analysis toward flexible architecture. In Section 4, we present our results and discuss their implications. Finally, in Section 5, we conclude the paper and note the future research directions.

2. Literature review

This section presents related studies in the literature on CPUMS and design requirement engineering approaches to complex system modeling.

2.1. Cyber physical urban mobility system

CPUMS have attracted the attention of the research community, with very recent research being published in major international peer-reviewed journals. For example, in response to the rapid population growth and increasing number of vehicles in cities in developing countries, the authors (Samalna et al., 2023a) conducted an analysis of the challenges and opportunities of implementing CPS to improve urban mobility management. And for the first time, the new paradigm "Cyber-Physical Urban Mobility Systems" appeared in the article by Samalna et al. These authors use this paradigm to refer to the strong integration of urban mobility systems with CPS.

The authors (Pundir et al., 2022) were interested in their studies on the contribution of transport networks with CPS in smart cities. The authors tried to understand intelligent transport systems combined with CPS, their conceptual framework, connected and automated vehicles, and other related communication technologies and networks. The authors formulated a perspective on urban mobility in future smart cities and the capabilities of CPS. The work carried out by the authors (Samalna et al., 2023b) provides an answer to the expectations of Pundir et al. by proposing an architectural framework for the design of a CPUMS, but for developing countries. Samalna et al. argue that cyber-physical-architectures are very recent approaches that aim to couple physical system architectures with algorithms to facilitate the control and management of complex interactions.

There is a research article presenting UTSC-CPS, a CPS for urban traffic lightscontrol (Zhang et al., 2020). The authors propose to a system for decision-makers and researchers to construct and simulate different types of traffic scenarios, rapidly develop and optimize new control strategies. The UTSC-CPS system allows effective control strategies to be applied to real traffic management. Moreover, what is very interesting, is that this new system consists of an architecture that fuses private cloud computing and edge computing, which effectively enhances the software and hardware performance of the urban traffic light control system, and achieves the perception and protection of information security in the cloud and devices, respectively, within the fusion framework.

Research by Tariq (2024) explores the transformative potential of smart transportation systems in sustainable urban mobility. As cities face rapid urbanization and environmental challenges, digital transportation offers solutions by leveraging advanced technologies to enhance transportation efficiency, reduce environmental impacts, and improve urban livability. Tariq examines the components, functionalities, and benefits of smart transportation, highlighting their role in traffic management, public transport, logistics, and urban planning.

Studies by Alahi et al. (2023) examine the challenges cities face in providing convenient, secure, and sustainable lifestyles amid growing urbanization and population. The Internet of Things (IoT) offers a solution by connecting physical objects through electronics, sensors, and communication networks, transforming smart city infrastructures. Alahi et al. (2023) review smart cities, detailing their characteristics and the IoT architecture, and analyzes various wireless communication technologies suitable for specific applications. The authors also discuss AI algorithms relevant to smart city scenarios and the integration of IoT and AI, highlighting the role of 5G networks in enhancing urban environments. They emphasize the opportunities created by combining IoT and AI to improve urban living quality, sustainability, and productivity, providing insights into the future of smart cities and their positive impact on urban residents.

The work of Conrad et al. (2023) discusses Intelligent Vehicular Cyber-Physical Systems (ICPSs) that enhance the reliability, efficiency, and adaptability of urban mobility systems, particularly in the context of autonomous transportation in smart cities, such as self-driving cars and advanced air mobility. However, the deployment of ICPSs raises concerns regarding safety, cybersecurity, communication reliability, and data management, necessitating specialized platforms to handle their complexity. Conrad et al. introduce a comprehensive CPS designed to explore, develop, and test ICPSs and related algorithms. This customizable embedded system utilizes a field programmable gate array connected to a supervisory computer for networked operations and supports advanced multi-agent algorithms.

Komminos et al. (2022) discuss the emergence of smart cities as a new urban paradigm characterized by data-driven efficiency and innovation in city operations. However, Komminos et al. (2022) identify two main weaknesses: the compartmentalization of solutions across various sectors (energy, transport, governance) leading to limited interoperability, and a generally low impact on efficiency and sustainability. The authors address these challenges by proposing the concept of “Connected Intelligence Spaces” within smart city ecosystems, which encompass physical, social, and digital dimensions. These spaces facilitate innovation and synergies among human, machine, and collective intelligence, focusing on improving efficiency through innovation rather than mere optimization. The authors hypothesize a universal architecture for impactful smart city projects, supported by connected intelligence spaces and cyber-physical-social systems of innovation. This hypothesis is evaluated through empirical case studies related to safety transportation, and positive energy districts. The authors highlight operational elements that contribute to high efficiency and identifies commonalities and innovation functions across sectors, ultimately defining a cohesive architecture for promoting innovation and performance in smart city ecosystems.

Zhang et al. (2016) proposed a CPS with heterogeneous model integration, based on extremely-large multi-source infrastructures in the Chinese city of Shenzhen. Zhang et al. formulated a mathematical optimization problem on the process of optimal integration of heterogeneous data models, namely model heterogeneity, input data sparsity or unknown ground truth. The authors have developed a real-world application called Speedometer, which infer real-time traffic speeds in urban areas.

In fact, the studies carried out by the various authors are very interesting, but they do not address the optimization of complex interactions in the development cycle of CPUMS, which is also a very complicated task. In reality, these complex engineering systems integrate a multitude of heterogeneous components or systems in permanent interaction and a complexity of transversal aspects of CPS, as well as local contexts of cities to be taken into account.

2.2. Design and requirement engineering approach for complex system modeling

The study of requirements engineering approaches has been a very active research topic over the past few decades (Aji et al., 2021). The requirements engineering approach provides a structured and methodical way of modeling complex systems such as CPUMS. It ensures that the resulting system meets the needs of its stakeholders and can effectively address the challenges of the system. Many studies have demonstrated the importance of the systems engineering approach to the design of complex systems (Bennett et al., 2023). The commonly used engineering tools are Unified Modeling Language (UML), System Modeling Language (SysML), Model-Based Systems Engineering (MBSE), and DSM tools (Akundi and Lopez, 2021). These tools have their own strengths and weaknesses, and the choice among them depends on the specific needs of the project (Madni and Sievers, 2018). For example,

- UML is a software modeling language (Savary et al., 2023);
- The SysML approach provides a formalized approach to system design (Shaofan et al., 2019);
- The MBSE approach provides a more formalized approach to system design (De Saqui-Sannes et al., 2022);
- The DSM tool is very useful for managing complexity in large-scale systems (Moran et al., 2021).

Each of these approaches has its own unique characteristics and can be used to address different aspects of system design. Ultimately, the choice between these approaches will depend on factors such as the size and complexity of the system to be designed, the level of formality required in the design process, and the specific needs of the project.

So, in particular, the DSM tool plays a crucial role in integrating components or subsystems and understanding complex dependencies or interactions between these system components (Zheng et al., 2019). However, DSM is an engineering method that enables innovative and systematic design of complex systems by identifying system interactions with the aim of simplifying understanding and reducing project risks (Guan et al., 2021). Several important critical issues have been identified as fundamental aspects of CPS, including integration, modularity, flexibility, sustainability (Kaur and Chatterjee, 2022). Efforts are underway to develop integrated, flexible and sustainable systems that take into account the local aspects of countries (Samalna et al., 2023a).

Recent research has also highlighted the importance of simplifying the interactions between system components in order to manage the complexity of multi-parameter system design and to enable easy understanding of the design loads on the system. By simplifying the interactions between the components of a system, engineers can better manage and avoid complexity. When working on complex engineering systems, it is important to address and resolve complexity. However, these systems can become so complex that their development becomes risky and may even be abandoned. This will reduce delays and improve the smooth running of the project. For example, Yassine et al. (Yassine and Braha, 2003) propose a unified modeling approach based on the DSM method to represent complex task relationships for better planning and managing project managers' initiatives. Other studies have measured the strength of interaction between teams and grouped organizational units to reduce coordination complexity (Yang et al., 2013).

Several other works have explored the use of DSM in urban transport systems, including ours (Farid et al., 2021), which proposed to study the impact of integrating electric vehicles in Abu Dhabi on the intelligent transportation system through a multi-domain matrix. This resulted in the need to coordinate traffic and energy management functions for an intelligent transport-energy system. Other studies have constructed the DSM from a conceptual model of urban well-being in relation to health (Hoffmann et al., 2020). The authors concluded that the DSM tool is powerful in supporting the development of integrated models for urban systems. For the same reason, the DSM is being used in other multidisciplinary and complex domains. Buzuku et al. (2016) conducted a case study using DSM on the formulation and analysis of policies related to a large industrial wastewater treatment plant in Brazil. Buzuku et al. concluded that DSM can drive the entire structure of the organizational's management system towards sustainability by improving the performance and efficiency of policies.

Overall, the use of the DSM with advanced techniques in the design and optimization of a CPUMS for developing countries can provide a systematic and comprehensive approach to addressing the challenges and specificities of these contexts. It allows scientists and engineers to identify the critical dependencies and bottlenecks, and to propose optimization strategies to improve the efficiency, sustainability, and responsiveness of the system.

2.3. Necessity of CPUMS in developing countries

Meeting the mobility needs of populations in urban environments in developing countries is becoming increasingly complex over time due to factors such as rapid population growth and delayed initiatives to alleviate mobility problems. This has led many researchers and urban planners to consider urgent and scientific measures to address issues such as congestion, road accidents, last-mile problems, air pollution, transport costs, and accessibility to different modes of transport (Olugu, 2017). Indeed, developing countries face significant developmental disparities and often encounter various socio-economic crises. Nevertheless, some African countries, such as Nigeria, Senegal, Côte d'Ivoire, South Africa, Morocco, Kenya, Ethiopia, Cameroon, and more are investing in the renewal of urban roads and new initiatives in sustainable mobility (Mboup, 2019).

The implementation of CPUMS in developing countries faces numerous legal, political, and regulatory challenges that can hinder their successful deployment. This paper provides exhaustive policy recommendations to address these barriers and facilitate the effective integration of CPUMS in urban settings.

a) Data Privacy and Security Laws: Clear guidelines for data collection, storage and sharing are essential to ensure user confidentiality and prevent misuse of sensitive information. Data protection laws in line with international standards must also be put in place to increase user and stakeholder confidence.
b) Intellectual Property Rights: Regulations need to be put in place to clarify the ownership and use of intellectual property in CPUMS technologies to encourage

innovation and investment. In addition, licensing and technology transfer mechanisms need to be established to facilitate the uptake of CPUMS solutions.

c) Interagency Coordination: Encourage the creation of a centralized authority or task force to coordinate CPUMS initiatives across different government departments in order to simplify decision-making processes. Encourage cooperation between local, regional and national authorities to ensure a consistent approach to urban mobility planning.

d) Policy Alignment: Ensure that CPUMS policies are aligned with broader urban development objectives, environmental concerns and social equity to maximize the positive impact of the system on urban communities. Decision-makers must also engage in dialogue with industry experts and researchers to keep abreast of emerging trends and best practices in CPUMS implementation.

e) Standardization: It recommends facilitating public-private cooperation by offering regulatory support and risk-sharing mechanisms to attract private sector participation in CPUMS deployment.

f) Funding and Investment: It aims to facilitate public-private cooperation by offering regulatory support and risk-sharing mechanisms to attract private sector participation in the deployment of CPUMS.

However, transforming mobility is becoming a necessity to align with the digital convergence and sustainable development policies advocated by the United Nations for the well-being of all cities worldwide. Moreover, there are compelling reasons to adopt cyber-physical technologies in urban mobility (Pundir et al., 2022):

a) Optimization of transport infrastructure: CPS can help optimize the use of existing transport infrastructure by monitoring and efficiently managing traffic, traffic lights, public transport, etc. This can help reduce congestion and improve traffic flow.

b) Improvement of road safety: CPS systems can be used to monitor road conditions in real-time, detect accidents and potential incidents, and warn drivers, to improve road safety.

c) Smart parking management: CPS can be used to manage parking land use more effectively by monitoring parking spaces, directing drivers to available spaces, and facilitating electronic payment.

d) Optimization of public transportation: CPS systems can be used to improve the planning and management of public transport networks, leading to improved accessibility in peripheral areas, reduced waiting times, and optimized routes.

e) Reduction of pollution and emissions: By optimizing traffic flow and encouraging the use of more sustainable modes, CPS can help reduce air pollution and greenhouse gas emissions associated with urban mobility.

f) Integration of alternative modes of transportation: CPS can facilitate the integration of alternative modes of transport such as bicycles, animals, canoes, etc., thus providing citizens in developing countries with more diverse and sustainable travel options.

The design of the CPUMS architecture is a significant challenge in systems engineering (Fritzsch et al., 2023). It requires a deep understanding of the complex interactions between the physical and digital components of the overall system.

3. CPUMS architecture design for developing countries

This section presents the multi-level analysis of the system, the analysis of relationships and dependencies between system components, and the presentation of component-oriented architecture.

3.1. Multi-level analysis of the CPUMS system

The CPUMS system involves a significant number of relationships, dependencies, and complex interactions between physical and cyber components. A multi-level analysis at macro, meso, and micro levels is required to identify the various components. **Figure 1** illustrates macro, meso and micro analysis of the CPUMS.

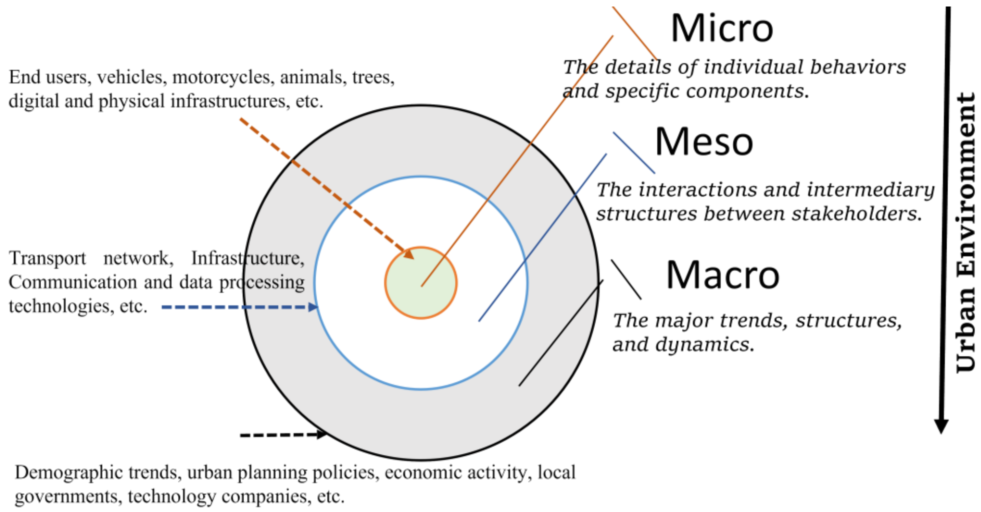


Figure 1. Proposed methodology.

The macro-level analysis of CPUMS includes household travel surveys, traffic counts, and transport modeling. It involves the study of large-scale travel patterns within the urban area. It clarifies transport and urban planning policies, and, most importantly, understands the key trends, structures, and dynamics that influence the system as a whole on, a broader and more strategic scale. The meso-level analysis of CPUMS is an intermediate level between macro analysis (which examines the system as a whole) and microscopic analysis (which focuses on individual components of the system). This analytical approach focuses on travel flows and public policies, and in particular on understanding the structures, dynamics, and interactions at a scale larger than that of individuals or isolated components, but smaller than that of the whole system. The micro-level analysis of CPUMS focuses on individual travel behaviors and decisions. It examines the factors that influence transport choices, such as cost, time, convenience, and personal preferences. It also focuses on specific individual components and interactions that shape the functioning of this system at a very detailed level.

In terms of scope, research and data collection, by focusing interviews and surveys on elements of multi-level analysis of urban space, we were able to capture the complex dynamics and interactions in urban mobility systems in developing countries. We generated an extensive dataset of CPUMS components and/or subsystems. Data cleansing allowed us to select a sample of 90 physical and cyber components for this study.

3.2. CPUMS components

The multi-level analysis in Section 3.1 has facilitated the identification of 90 key components for the design of the CPUMS architecture in the context of developing countries. **Figure 2** shows the list of components according to the levels of analysis.

No	Components
1	Roads
2	Wireless communication infrastructure for intelligent transportation systems (ITS)
3	Traffic management and control centers
4	Adaptive traffic signal control systems
5	Transportation data exchange platforms
...	...
86	Transportation asset management databases and geographic information systems (GIS)
87	Automated fare collection (AFC) systems and contactless payment solutions
88	Transportation network infrastructure and multimodal connectivity
89	Telecommunications infrastructure and cellular network coverage
90	Vehicle maintenance facilities and fleet management operations

Figure 2. The set of 90 components in CPUMS design.

3.3. Component-oriented architecture representation of CPUMS

The CPUMS consists of several components that collect urban data and automatically analyze it to make decisions in case of accidents or incidents. Most of the components are able to communicate with each other, and others perform computations. **Figure 3** provides an overview of the CPUMS component diagram.

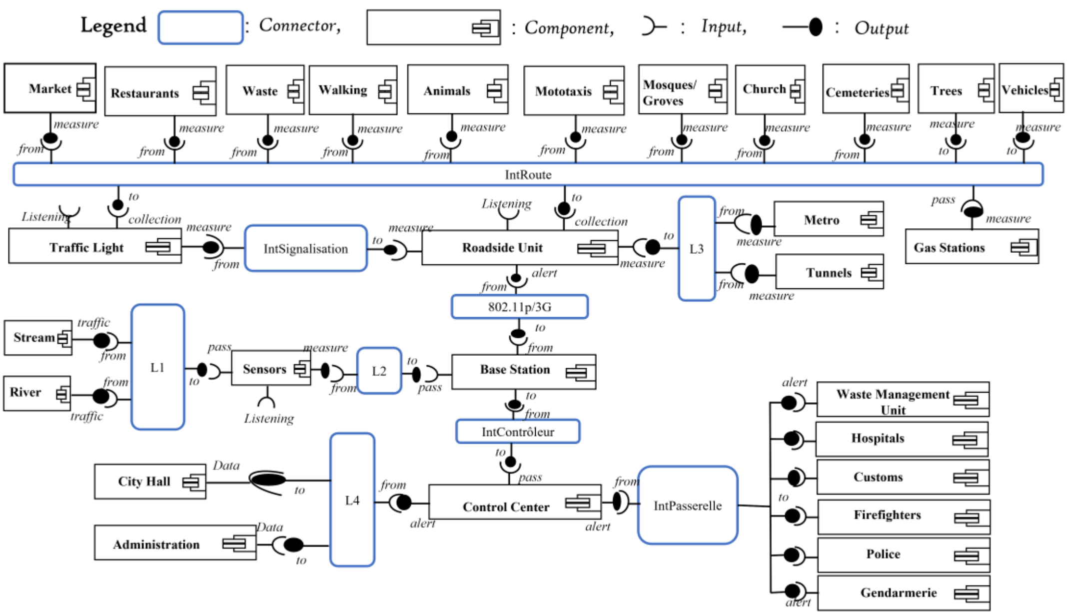


Figure 3. CPUMS architecture based π-ADL description.

Figure 3 primarily illustrates the interactions between the system components. Components interact with each other through connectors. A connector connects the component to other components and to the component's environment. This graphical representation provides an overview of the system components and their interactions.

- The components Walking, Restaurants (with the back-turning), Waste, Walking, Animals, Mototaxis, Mosques (and even the Groves), Churches, Cemeteries, Trees, Vehicles, Gas stations are sources of urban mobility Big Data. These data can pass through the IntRoute connector to be used by the Traffic lights and even the Roadside unit.
- The Sensor components collect physical data from the River, Stream components via the L1 connector and transit it to the Base station via the L2 connector.
- The urban environment is represented by connectors L1, L2, L3, L4, IntGateway, IntRoute, 802.11p/3G, IntController, and IntSignaling. L1, L3, L4, and IntRoute bring new metrics to the system. L2 facilitates the exchanges between the Sensor component and the Base station component. Similarly, IntGateway facilitates the transmission of alerts from the Control center to components such as Waste management unit, Hospitals, Customs, Firefighters, Police, and Gendarmerie regarding emergency situations on the urban road network. The 802.11p/3G connection acts as an interface between the Roadside unit and the Base station. Finally, IntController acts as an interface between the Base station and the Control center.
- IntSignaling links the Traffic lights component with the Roadside unit component to enable in-depth traffic analysis by the Control center component. This link enables optimal decision-making with regard to road signaling.
- The City Hall and Administration components receive data related to urban mobility for use via the L4 connector, provided by the Control center. The Mototaxis components operating in the urban environment fall under the jurisdiction of the Town hall component and are required to pay municipal taxes in a timely manner. In addition, the Administration component requires exploratory analyses of urban mobility in order to make decisions aimed at improving public policies in the field of urban transport. Here, the Administration refers to the senior divisional officer or Governor.

4. CPUMS-based DSM and K-Means clustering

4.1. Clustering and dependency modeling methods

This section introduces clustering and dependency modeling in the context of the CPUMS architecture, and also introduces mathematical concepts of K-Means and DSM.

4.1.1 Clustering algorithms

In the context of the CPUMS architecture, clustering is an essential method for grouping urban mobility components into meaningful subsets. The aim is to understand the relationships between components, which will enable a better understanding of mobility flows, interactions between different system components, and user needs.

Clustering is a fundamental technique in data analysis and machine learning used to group similar objects or data points into clusters. Clustering algorithms such as K-Means, K-Medoids, DBSCAN (Density-Based Spatial Clustering of Applications with Noise), OPTICS (Ordering Points To Identify the Clustering Structure), hierarchical clustering, and fuzzy C-Means are common examples of methods used to group data into meaningful clusters (Ahmed et al., 2020). These techniques are used in various domains such as marketing, social networks analysis, medicine, and engineering to extract useful information from complex datasets. There are various clustering algorithms available, each with its own strengths, weaknesses, and applications. The **Table 1** shows comparison between the popular clustering algorithms in the literature.

Table 1. Summary of clustering algorithms related works.

Algorithm	Authors	Simple	Assume spherical clusters	Robust to noise and outliers	Time complexity
K-Means	(Kansal et al., 2018)	Yes	Yes	No	O (k. n. d)
K-Medoids	(Wang et al., 2019)	No	No	Yes	O (k.(n-k)^2)
DBSCAN	(Liu et al., 2020)	No	No	Yes	O (n log n)
OPTICS	(Agrawal., 2016)	No	No	No	O (n log n)
Hierarchical Clustering	(Murtagh and Contreras, 2017)	No	No	No	O (n^2 log n)
Fuzzy C-Means	(Kolen and Hutcheson, 2002)	No	No	Yes	O (c. m. n)
Mean-Shift	(Tehreem et al., 2019)	No	No	Yes	O (n^2)
Agglomerative Clustering	(Karthikeyan et al., 2020)	No	No	No	O (n^3)

Thus, clustering techniques such as K-Means are simple and can facilitate intuitive analysis to efficiently group CPUMS components into clusters, enabling trend detection, resource planning, and informed decision-making to optimize the overall system. However, the K-Means algorithm requires a priori determination of the optimal number of clusters, K, to achieve an optimal partition. Consequently, several techniques can be used for this purpose. **Table 2** presents these techniques, which are widely used in partition evaluation. Cluster evaluation plays a crucial role in clustering analysis by helping to evaluate the quality of the clustering results' quality. There are a variety of evaluation methods, each with its own set of advantages and disadvantages. This table shows the common usage status of each method.

Table 2. Summary of clustering evaluation methods.

	Evaluation method	Measures	Authors
1	Silhouette Score	Compactness and separation	(Hartama and Anjelita, 2022)
2	Davies-Bouldin Index	The average similarity between each cluster and its most similar cluster	(Bagirov et al., 2023)
3	Calinski-Harabsz Index	The ratio of between-cluster dispersion to within-cluster dispersion	(Ashari et al., 2023)
4	Dunn Index	The compactness and separation of clusters	(Misuraca et al., 2019)
5	Rand Index, Fowlkes-Mallows	The similarity between two clusters	(Campello, 2007)
6	Jaccard Index	The similarity between two sets	(Tang et al., 2021)
7	Purity score	The purity of clusters	(Kim et al., 2016)

Table 2. (*Continued*).

	Evaluation method	Measures	Authors
8	Entropy	The uncertainty or randomness of clusters	(Xu et al., 2018)
9	Homogeneity, Completeness, V-Measure	The homogeneity, completeness, and harmonic mean of both	(Aljarah et al., 2021)
10	Elbow method	A suitable number of clusters that balances the trade-off between model complexity and clustering quality	(Shi et al., 2021)

The Calinski-Harabasz Index, also known as the Variance Ratio Criterion, is often used to evaluate clustering results, especially in scenarios where the ground truth labels are not available. It measures the ratio of the inter-cluster variance to the intra-cluster variance, which essentially assesses the compactness and separation of the clusters. For K clustering in CPUMS, the choice of the Calinski-Harabasz Index can be advantageous for several reasons:

1) Interpretability: The index provides an intuitive measure of clustering quality by quantifying the compactness and separation of clusters. In the context of urban mobility systems, where understanding the spatial distribution and separation of different mobility patterns is critical, this interpretability can be valuable.
2) Scalability: The Calinski-Harabasz Index is relatively computationally efficient and can handle large datasets, which is essential for analyzing mobility data in urban environments where the volume of data can be substantial.
3) Robustness: The index is robust to noise and outliers, which is beneficial in real-world scenarios where mobility data may contain irregularities or anomalies.
4) Automation: Since the Calinski-Harabasz Index does not require ground truth labels, it can be applied in an unsupervised manner, making it suitable for situations where manual labeling of data is impractical or unavailable.
5) Comparison: The index allows for the comparison of different clustering solutions by providing a numerical measure of their quality. This is particularly useful when exploring different clustering algorithms or parameter settings to identify the most appropriate clustering approach for urban mobility systems.

Overall, the Calinski-Harabasz Index provides a comprehensive and practical means of evaluating clustering solutions for K-clustering in CPUMS, making it a suitable choice to guide decision-making and system optimization in such contexts.

4.1.2 Dependency modeling methods

In the context of the CPUMS architecture, dependency modeling aims to represent the relationships and interactions between the various components of the CPUMS, such as mototaxis, infrastructure, users, and services. This modeling enables the visualization and analysis of functional dependencies, information flows, and interconnections among the constituent components of the CPUMS.

DSM is an engineering tools that systematically maps dependencies between components, facilitating the understanding of interactions and information flows within the CPUMS. This approach helps identify critical dependencies, prioritize elements based on their impact, and optimize the design and organization of the CPUMS architecture. Thus, dependency modeling of the CPUMS architecture provides a structural framework for analyzing and visualizing interdependent relationships among components, which is essential for effective design, optimization, and validation of the architecture in the context of urban mobility.

4.2. Theoretical foundation of the mathematical concepts

4.2.1. Dependency Structure Matrix

Mathematically, a Dependency Structure Matrix (DSM) is a matrix representation of the interactions and dependencies between components in CPUMS. It provides a systematic representation of the dependency relationships, information flows, and interconnections among the components of CPUMS. By denoting X as a matrix, which is an $n \times n$ matrix, where n represents the number of components in the system (Browning, 2015). Equation (1) is the mathematical representation of the square matrix X:

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nn} \end{pmatrix} \tag{1}$$

where x_{ij} represents the value of the cell located in row i and column j of matrix X. This value can be based on various criteria such as the frequency of interaction between elements, the importance of the relationship, the dependency between elements, etc. This value can also be numerical, symbolic, or qualitative depending on the context of the design structure matrix. The relevance of DSM to this study lies in its ability to provide an overview of the interdependencies between different components of the urban mobility architecture. By identifying functional dependencies, critical interactions, and information flows within the system, the DSM allows us to prioritize components or subsystems, optimize the architecture design, and gain a better understanding of the impact of interconnections on overall system performance.

4.2.2. K-Means clustering method

The K-Means algorithm its ability to efficiently cluster CPUMS components into meaningful clusters. It's based on the principle of minimizing intra-cluster variance, denoted by the objective function J which attempts to minimize the sum of squared distances between each data point x_i and the centroid x_j of its assigned cluster (Kansal et al., 2018):

$$J = \sum_{i=1}^{n} \sum_{j=1}^{k} \left\| x_i - c_j \right\|^2 \tag{2}$$

where n is the total number of data points, k is the number of clusters, x_i is the i-th data point, c_j is the centroid of the j-th cluster, and $\|.\|$ is the Euclidean distance.

The K-Means algorithm iterates through two main steps (Kansal et al., 2018):

Step 1: Assignment: Each data point is assigned to the cluster with the nearest centroid based on Euclidean distance.

Step 2: Update: Cluster centroids are updated by calculating the average of all data points assigned to each cluster.

This iterative process continues until convergence, where the centroids and data point assignments stabilize. The K-Means algorithm will allow us to uncover behavioral patterns, segment mobility flows based on relevant criteria, and identify homogeneous groups of entities related to urban mobility. This approach, rooted in mathematical optimization principles, will help us better understand mobility dynamics, optimize the design of our architecture, and make informed decisions to improve the system as a whole.

4.2.3. Integration of PCA for DSM dimensionality reduction

This section presents the integration of PCA with DSM for the purpose of CPUMS component dimensionality reduction and relevant feature extraction.

Dimensionality reduction and relevant Features in CPUMS DSM

PCA is used to transform the CPUMS DSM, which consists of n observations (components), into a set of fewer variables called principal components. This dimensionality reduction allows the high-dimensional DSM of the CPUMS to be transformed into a lower-dimensional space while preserving as much information as possible. By retaining the principal components that explain the most of the variance in the data, we can effectively reduce the dimensionality of the DSM and extract the most relevant features for further analysis.

PCA is based on computing the eigenvectors and eigenvalues of the covariance matrix of the data. Let X be the data matrix, where each row represents a component and each column represents an observation. The first step in PCA is to center the data by subtracting the mean of each variable. Then, the covariance matrix $\sum$ is computed as follows (Helwig et al., 2017):

$$\sum = \frac{1}{n-1}(X-\bar{X})\,(X-\bar{X})^T \tag{3}$$

where $\bar{X}$ is the mean vector of the columns of X, and n is the total number of observations.

Next, the eigenvectors $v_1, v_2, \ldots, v_p$ and the corresponding eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_p$ of the covariance matrix are computed. The principal components are obtained by projecting the original data onto the eigenvectors, thus providing a new representation of the data in a lower-dimensional space. The projection of the original data onto the eigenvectors is given by (Deegalla et al., 2006):

$$PC_i = X \times v_i \tag{4}$$

where PC_i represents the i-th principal component, and v_i is the i-th eigenvector.

In general, the principal components are ordered by decreasing amount of variance explained, so that the first components capture the largest amount of variance in the data. This transformation reduces the dimensionality while retaining as much information as possible, making data analysis and visualization easier.

Optimization of DSM CPUMS architecture based PCA

By extracting the most relevant features from the data, PCA allowed us to gain a deeper understanding of the underlying structures and relationships between the variables in the system. This deep understanding has helped us optimize the architecture design by focusing on the most informative and discriminative features. PCA identifies the principal components that capture the maximum variance in the data.

Let X be the data matrix representing the DSM of the CPUMS, where each row corresponds to a component and each column corresponds to a variable. The PCA process can be as follows:

Step 1. Standardization of the data: Each variable x_i is standardized $\tilde{x}_i$ to have a mean of 0 and a standard deviation of 1 to ensure that all variables contribute equally to the analysis (Milligan et al., 1988).

$$\tilde{x}_i = \frac{x_i - \bar{x}_i}{\sigma_i} \tag{5}$$

where

$$\tilde{x}_i = \frac{1}{n}\sum_{k=1}^{n} x_{ki}, \text{ for } i \text{ ranging from 1 to } n \tag{6}$$

$$\sigma_i = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(x_{ji} - \bar{x}_i)^2}, \text{ for } i \text{ ranging from 1 to } n \tag{7}$$

x_i a vector of size p containing the values of p variables for observations i, x_{ki} the value of variable x_i in the k-th observation, x_{ji} the value of variable x_i in the j-th observation.

Step 2. Calculation of the covariance matrix: The covariance matrix of the standardized data is computed, where the (i, j)-th element represents the covariance between variables i and j.

$$C = cov(\tilde{x}_i, \tilde{x}_j) = \frac{1}{n-1}\sum_{k=1}^{n}(\tilde{x}_{ki} - \bar{x}_i) \times (\tilde{x}_{kj} - \bar{x}_j) \tag{8}$$

where n represents the number of observations in the dataset X, the variable k in the sum indicates that we iterate through the observations, calculating the covariance between the standardized variables $\tilde{x}_i$ and $\tilde{x}_j$ for each pair of variables i and j, where $\bar{x}_i$ and $\bar{x}_j$ denote the means of the values of the variable x_i and x_j respectively, $\tilde{x}_{ki}$ and $\tilde{x}_{kj}$ represent the standardized values of the respective variables x_i and x_j for the k-th sample.

Step 3. Eigen decomposition of the covariance matrix: The covariance matrix $\sum$ is then decomposed into its eigenvectors $v_1, v_2, \ldots, v_p$ and eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_p$. The eigenvectors represent the directions of maximum variance in the data, and the eigenvalues indicate the amount of variance explained by each eigenvector (Abdi, 2007).

$$Z_k = \sum_{i=1}^{n} v_{ki} \times \tilde{x}_i, \text{ for } k = 1 \text{ to } p \tag{9}$$

where n is the total number of observations in the dataset X. $\tilde{x}_i$ is the standardized value of the variable x_i for the i-th observation. v_{ki} is the i-th component of the eigenvector v associated with the k-th principal component. p is the total number of principal components.

Step 4. Selection of principal components: The principal components are selected based on their corresponding eigenvalues. Components with higher eigenvalues capture more variance in the data and are retained for further analysis (Boutsidis et al., 2008).

Step 5. Projection of data onto principal components: The original data matrix X is projected onto the selected principal components to obtain the transformed data matrix X', where each column represents a principal component (Salem, 2021).

$$Z = X \times V_k \tag{10}$$

where Z is the projected data matrix of size n x k, V_k is a matrix of size p x k containing the first k eigenvectors (principal components) of the covariance matrix or correlation matrix of the data.

By optimizing the DSM CPUMS architecture based on PCA, we focus on retaining the principal components that capture the most significant variability in the data. This allows us to simplify the representation of the CPUMS architecture while preserving essential information about its underlying structure and relationships among variables. The optimized architecture design enhances the interpretability and effectiveness of the CPUMS, resulting in improved decision-making and system performance.

5. Results and discussions

5.1. Representation of the CPUMS DSM

The CPUMS DSM represents the interdependencies and relationships between the various components of the system, revealing its structural complexity. **Figure 4** shows the CPUMS DSM.

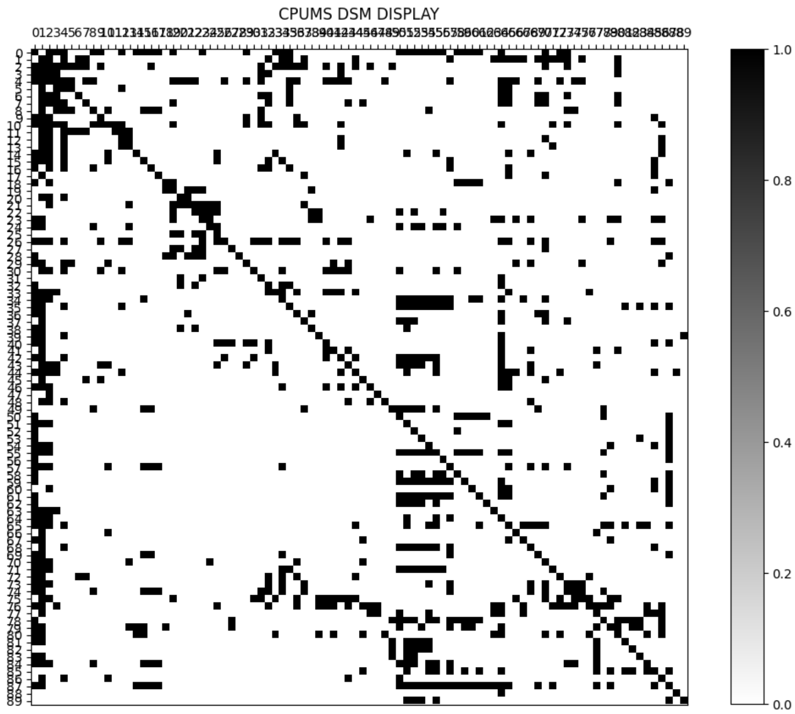


Figure 4. CPUMS DSM representation.

The CPUMS DSM is derived from the set of 90 components identified in **Figure 2**. We then identified the relationships between these different components based on information collected from stakeholders, experts, observations, and a literature review.

These relationships were coded in the form of a binary matrix, where a “1” entry indicates an interaction between two components, and a “0” entry indicates the absence of an interaction. The resulting CPUMS DSM provides a clear visualization of the interdependencies within the CPUMS.

5.2. CPUMS DSM dimensionality reduction using PCA

Figure 5 shows the new matrix representation of the CPUMS, obtained by the applying PCA.

	0	1
0	1.619425	-2.748846
1	-1.387381	-1.642803
2	-1.672957	-1.690555
3	-0.916600	0.106117
4	-1.849524	-1.703048
...	...	...
85	1.373535	0.120782
86	-0.233367	0.530750
87	2.541505	-1.772034
88	-0.192576	0.959273
89	1.241812	0.774625

90 rows × 2 columns

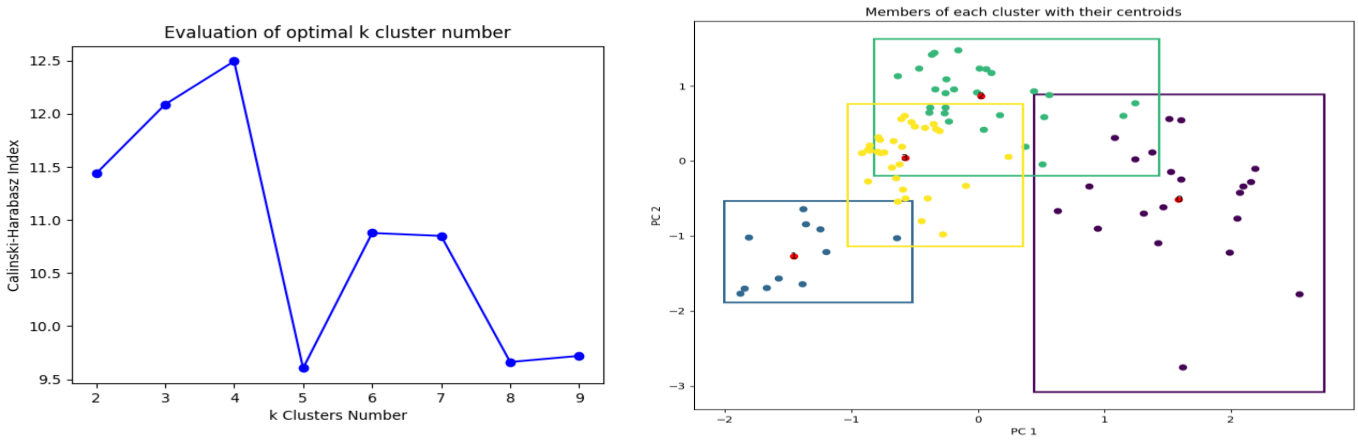
Figure 5. CPUMS DSM-based PCA.

PCA enabled the capture of the most significant dependency patterns between the different components of the CPUMS. By reducing the dimensionality of the matrix representation while preserving the essential information, this new representation facilitates the interpretation of the complex interactions within the system. The two principal components resulting from the PCA thus summarize the main sources of variance in the interactions between the CPUMS components.

5.3. PCA DSM optimized clustering-based Calinski-Harabsz index

Figure 6a allows us to identify the number of clusters on the plot where the Calinski-Harabasz index reaches its maximum value. Thus, the integer value of four corresponds to the maximum number of clusters, and provides an indication of the number of distinct groups present in the data.

Figure 6b shows on a two-dimensional plane the four clusters identified from the reduced PCA CPUMS DSM matrix. The centroids of each cluster are represented by numbered red points from 0 to 3. The data points belonging to each group are respectively represented by black, blue, yellow, and green, respectively. **Table 3** shows the components that make up each of the four clusters identified following the analysis of the PCA-based matrix representation of the CPUMS. These clusters group together components with similar characteristics and interactions within the system.



(**a**) (**b**)

Figure 6. (**a**) The optimal clusters number with Calinski-Harabsz Index; (**b**) the 2D principal component plot of CPUMS elements.

Table 3. List of cluster members with their centroid.

Cluster	Cluster members
0	0, 24, 34, 35, 42, 43, 49, 55, 58, 59, 61, 62, 65, 68, 71, 78, 79, 81, 84, 85, 87
1	1, 2, 4, 6, 7, 10, 26, 33, 74, 75, 76
2	18, 19, 21, 22, 25, 27, 28, 31, 32, 37, 38, 47, 50, 52, 53, 54, 56, 60, 64, 66, 67, 69, 82, 83, 88, 89
3	3, 5, 8, 9, 11, 12, 13, 14, 15, 16, 17, 20, 23, 29, 30, 36, 39, 40, 41, 44, 45, 46, 48, 51, 57, 77, 80, 86

- Cluster 0 covers the basic elements of transportation infrastructure, with a focus on non-motorized transport modes, intelligent traffic management, traffic safety, flow optimization, and geospatial integration.
- Cluster 1 primarily groups the components related to communication and information systems, as well as public transport services. This suggests that these elements of the CPUMS are highly interconnected and form a coherent subsystem within the overall urban mobility system.
- Cluster 2 covers a very broad and integrated vision with a wide range of technologies and infrastructures related to intelligent and sustainable transportation systems.
- Cluster 3 focuses on the advanced operational, technological, environmental, and organizational dimensions of intelligent transportation systems, thus complementing the more infrastructural and sustainable mobility aspects of Cluster 2.

5.4. Discussion on the impact of the results

In terms of the DSM matrix, this construction has helped to visualize the interdependencies between the different components of the CPUMS, to provide ways to optimize the process of modular design and integration of the different system components, and to facilitate understanding, communication, and decision support for managing complexity during design and implementation. However, the stakeholders and engineers benefit from a powerful tool to better understand, structure, and manage the complexity of intelligent transportation systems, thus improving the quality of their decisions and the overall system performance.

The combination of DSM analysis with PCA has brought significant benefits: reducing the dimensionality of the DSM by identifying the principal components that contain most of the variance of the system, identifying the most important and influential components of the CPUMS by focusing on the priority elements. Thus, decision-makers benefit from a tool to reduce complexity, identifies priority elements, understands interdependencies, and optimizes the design of the CPUMS, thereby improving the quality and efficiency of their decision-making process.

The grouping of the CPUMS into 4 clusters provides a fundamental basis for informed decision-making, effective strategic planning, and coordinated implementation of intelligent transportation systems, thus contributing to more sustainable, efficient, and safer mobility. For example, Cluster 0 is concerned with all road infrastructure and non-motorized transport; Cluster 1 is concerned with sustainable mobility and travel management; Cluster 2 is related to intelligent and resilient infrastructure, and Cluster 3 is only interested in advanced ITS operations and services. Nevertheless, the numerical simulation has identified the following outlier that require special attention: Roads, Traffic management and control centers, Transportation data exchange platforms, Real-time scheduling and optimization for public transportation, Transportation network infrastructure and multimodal connectivity. They can provide valuable information for stakeholder decision support in the CPUMS.

For example, "Traffic management and control centers" may indicate reliability, performance or integration issues with that subsystem. They may indicate potential bottlenecks in the system, such as "Transportation data exchange platforms" or "Real-time scheduling and optimization for public transportation". They may also reveal elements that offer innovative opportunities, such as "Transportation network infrastructure and multimodal connectivity" to deploy new mobility solutions. They may also indicate an imbalance between elements, such as oversized "Roads" which can guide investment decisions and resource allocation to rebalance the system in a more optimal way.

6. Conclusion and future directions

In conclusion, this study has demonstrated the significant potential of integrating Cyber-Physical Systems (CPS) into urban mobility frameworks, especially in developing countries. By using the Dependency Structure Matrix (DSM) in conjunction with advanced techniques such as Principal Component Analysis (PCA) and outlier analysis, we have developed a robust methodology for understanding and optimizing the complex interdependencies inherent in Cyber-Physical Urban Mobility Systems (CPUMS). Our findings underscore the effectiveness of PCA in simplifying the representation of CPUMS, elucidating critical subsystems and interdependencies, and isolating the elements that carry the most informational weight. This improved understanding of system complexity has informed strategic decision-making, enabling more efficient resource allocation and targeted actions to address system vulnerabilities, bottlenecks, and opportunities for innovation.

The findings from outlier analysis have further highlighted the utility of these techniques in identifying areas of fragility and imbalance within the system, thus guiding stakeholders towards more informed and effective interventions. By using these analytical tools, transportation engineering professionals can significantly improve the quality and efficiency of their decision-making processes, ultimately leading to more sustainable and intelligent transportation solutions.

Future research should explore the integration of these methods with other analytical frameworks, such as scenario simulation and real-time data analysis, to further refine decision-making processes and enable dynamic adaptation to evolving urban mobility needs. In addition, extending the application of these approaches to other domains within engineering and complex systems management holds promise for uncovering new research avenues and practical applications. Overall, this study contributes to the advancement of digital transportation infrastructure in developing countries, promoting the creation of efficient, sustainable, and human-centered mobility solutions that can meet the demands of growing urban populations.

Author contributions: Conceptualization, DAS and VRN; methodology, DAS; software, DAS; writing—original draft, DAS; data curation, JMN; writing—review and editing, JMN; investigation, IT; visualization, AAAA and K; Supervision, K. All authors have read and agreed to the published version of the manuscript.

Data availability: The data used to support the findings of this study are available from the corresponding author upon request.

Acknowledgments: We thank the LaRI Team of the University of Maroua and the ISDM Research Team of the Faculty of Sciences of the University of Douala.

Conflict of interest: The authors declare no conflict of interest.

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