MOBILITY AS A SERVICE: SYSTEM OPTIMIZATION AND ITS DATA EXPLOITATION FOR CITY PLANNING

By

MSc. Eng. Taha Hatcha

A dissertation

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Supervised by:

Prof. Dr.-Ing. Jörg Rainer Noennig

Prof. Dr.-Ing. K. Mert Çubukcu

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Abstract

In a world fueled by digitalization, the amounts of data generated daily hold a big potential for improving decision-making processes, urban planning, and fostering sustainable and livable cities. However, most of this data remains uncollected and unanalyzed, resulting in missed opportunities for authorities and city planners. This research sought to exploit Mobility as a Service (MaaS) data to develop an approach that synthesizes meaningful insights from urban data and sheds light on the intersection of MaaS and city planning good practices.

The research delves into the details of MaaS, a fully digitalized system offering unparalleled opportunities for data collection and analysis. Through an exploration of the MaaS ecosystem, the study identified its main data sources, types, features, and their relevance to city planning. To concretely measure this relevance, the research strategically selects five key domains (innovation, resource management, collaboration, governance, and sustainability) from the Sustainable Development Goals (SDGs) and assesses the alignment of MaaS data keywords within these domains. The study went over two stages; the first took a sample of 50 companies, and the second covered 200 MaaS organizations. Employing a semantic approach, the study accurately selects pertinent keywords and extracts data from credible sources to delineate the significance of MaaS data in city planning contexts. Beyond mere analysis, the research advocates for the development of use cases based on MaaS-generated data. These use cases not only aid in comprehending and elucidating the vast troves of MaaS data but also illuminate opportunities for improvement and identify gaps in the urban decision-making landscape. Ultimately, the study aims to foster a more informed and effective decision-making system for urban environments.

By harnessing the power of data analytics and NLP, the MaaS system can be fine-tuned to better meet the needs of both users and cities, resulting in improved and more sustainable urban environments. The uncovered patterns within this study reveal the patterns of different MaaS systems and uncover the ways of their integration within the urban system. Findings indicate that advanced MaaS systems prioritize societal goals and resource management, mid-level systems emphasize innovation and collaboration, while the lowest level of integration pertains to governance and sustainability.

During this research, an unexpected turn of events occurred—the COVID-19 pandemic. Capitalizing on this unforeseen situation, the study explored the potential impact of advanced mobility systems on the spread of the pandemic. The central question is whether advanced mobility systems exhibit greater resilience against pandemics or play no significant role. To address this query, the research delved into the COVID-19 case data from various regions in Germany over two years, concurrently assessing the smart index for selected cities. The results revealed an interesting correlation. Cities with more advanced mobility systems exhibit fewer contamination cases during the pandemic. This correlation can be attributed to several factors, such as the presence of digital and advanced control systems, streamlined organizational structures, and the availability of alternative modes of transportation that reduce the likelihood of contamination. These findings can provide practical implications for the mobility domain and city planning.

In conclusion, this research validated the potential of MaaS data in optimizing urban systems and city planning. By capitalizing on the wealth of data generated by

MaaS companies, insights into societal goals, resource management, innovation, collaboration, governance, and sustainability were gained, and the relevant use cases in the city planning domain were also derived. Additionally, the unexpected exploration of the impact of advanced mobility systems on pandemic spread highlights the advantages offered by these systems in mitigating the effects of contagions.

Keywords

Mobility as a Service
Urban planning
Natural Language Processing
Machine Learning
Exploitation strategies
COVID-19

Kurzfassung

In einer Welt, die von Digitalisierung angetrieben wird, birgt die täglich generierte Datenmenge ein großes Potenzial zur Verbesserung von Entscheidungsprozessen, städtischer Planung und zur Förderung nachhaltiger und lebenswerter Städte. Dennoch bleibt der Großteil dieser Daten ungesammelt und nicht analysiert, was zu verpassten Chancen für Behörden und Stadtplaner führt. Diese Forschung versuchte, Mobility as a Service (MaaS) zu nutzen, um einen Ansatz zu entwickeln, der bedeutende Erkenntnisse aus städtischen Daten synthetisiert und Licht auf die Schnittstelle von MaaS und bewährten Praktiken der Stadtplanung wirft.

Die Forschung geht in die Details von MaaS, einem vollständig digitalisierten System, das beispiellose Möglichkeiten für Datensammlung und -analyse bietet. Durch die Erforschung des MaaS-Ökosystems identifizierte die Studie seine wichtigsten Datenquellen, -typen, -merkmale und ihre Relevanz für die Stadtplanung. Um diese Relevanz konkret zu messen, wählt die Forschung strategisch fünf Schlüsselbereiche (innovation, resource management, collaboration, governance, and sustainability) der Sustainable Development Goals (SDGs) aus und bewertet die Übereinstimmung von MaaS-Datenkeywords in diesen Bereichen. Die Studie umfasste zwei Phasen: Die erste nahm eine Stichprobe von 50 Unternehmen, und die zweite umfasste 200 MaaS-Organisationen. Unter Verwendung eines semantischen Ansatzes wählt die Studie genau relevante Schlüsselwörter aus und extrahiert Daten aus glaubwürdigen Quellen, um die Bedeutung von MaaS-Daten im Kontext der Stadtplanung zu umreißen. Über bloße Analyse hinaus setzt sich die Forschung für die Entwicklung von Anwendungsfällen auf der Grundlage von MaaS-generierten Daten ein. Diese Anwendungsfälle helfen nicht nur dabei, die umfangreichen Datenbestände von MaaS zu verstehen und zu erhellen, sondern auch Möglichkeiten zur Verbesserung aufzuzeigen und Lücken in der städtischen Entscheidungsfindungslandschaft zu identifizieren. Letztendlich zielt die Studie darauf ab, ein informierteres und effektiveres Entscheidungssystem für urbane Umgebungen zu fördern.

Durch die Nutzung der Kraft von Datenanalytik und NLP kann das MaaS-System optimiert werden, um den Bedürfnissen sowohl der Benutzer als auch der Städte besser gerecht zu werden und damit zu verbesserten und nachhaltigeren städtischen Umgebungen führen. Die aufgedeckten Muster innerhalb dieser Studie zeigen die Muster verschiedener MaaS-Systeme auf und enthüllen die Möglichkeiten ihrer Integration innerhalb des städtischen Systems. Die Ergebnisse deuten darauf hin, dass fortgeschrittene MaaS-Systeme gesellschaftliche Ziele und Ressourcenmanagement priorisieren, mittlere Systeme Innovation und Zusammenarbeit betonen, während die niedrigste Integrationsstufe Governance und Nachhaltigkeit betrifft.

Während dieser Forschung ereignete sich eine unerwartete Wendung - die COVID-19-Pandemie. Die Studie nutzte diese unvorhergesehene Situation, um das potenzielle Auswirkungen fortschrittlicher Mobilitätssysteme auf die Ausbreitung der Pandemie zu erforschen. Die zentrale Frage ist, ob fortschrittliche Mobilitätssysteme eine größere Widerstandsfähigkeit gegen Pandemien zeigen oder keine signifikante Rolle spielen. Um diese Frage zu beantworten, untersuchte die Forschung die COVID-

19-Falldaten aus verschiedenen Regionen Deutschlands über zwei Jahre und bewertete gleichzeitig den Smart Index für ausgewählte Städte. Die Ergebnisse zeigten eine interessante Korrelation. Städte mit fortschrittlicheren Mobilitätssystemen weisen während der Pandemie weniger Kontaminationsfälle auf. Diese Korrelation kann auf mehrere Faktoren zurückgeführt werden, wie das Vorhandensein digitaler und fortschrittlicher Kontrollsysteme, gestraffte Organisationsstrukturen und die Verfügbarkeit alternativer Transportmittel, die die Wahrscheinlichkeit von Kontaminationen verringern. Diese Erkenntnisse können praktische Implikationen für den Mobilitätsbereich und die Stadtplanung bieten.

Zusammenfassend validiert diese Forschung das Potenzial von MaaS-Daten zur Optimierung städtischer Systeme und der Stadtplanung. Durch die Nutzung der Fülle von Daten, die von MaaS-Unternehmen generiert werden, wurden Erkenntnisse zu gesellschaftlichen Zielen, Ressourcenmanagement, Innovation, Zusammenarbeit, Governance und Nachhaltigkeit gewonnen, und die relevanten Anwendungsfälle im Bereich der Stadtplanung wurden abgeleitet. Darüber hinaus unterstreicht die unerwartete Erforschung der Auswirkungen fortschrittlicher Mobilitätssysteme auf die Pandemieausbreitung die Vorteile dieser Systeme bei der Eindämmung der Auswirkungen von Infektionen.

Schlüsselwörter

Mobility as a Service
Stadtplanung
Natürliche Sprachverarbeitung
Maschinelles Lernen
Ausbeutungsstrategien
COVID-19

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AI: Artificial Intelligence
ANN: Artificial Neural Network
API: Application Programming Interface
BI: Business Intelligence
CAGR: Compound Annual Growth Rate
CMR: Community Mobility Reports
CSV: Comma Separated Values
DL: Deep Learning
DM: Data Mining
EDEN: Electronic Democracy European Network
GIS: Geographical Information System
IoT: Internet of Things
MaaS: Mobility as a Service
ML: Machine Learning
MPG: Miles per Gallon
MSPs: Mobility Service Providers
MT: Machine Translation
NLG: Natural language generation
NLP: Natural language processing
NLTK: Natural Language Toolkit
PaaS: Platform as a Service
PDF Portable Document Format
Post: Part-of-Speech Tagging
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PT: Public Transport
QRC: Quick Response Code
R&D: Research and Development
RAKE Rapid Automatic Keyword Extraction
RDBMS: Relational Database Management Systems
SARS: Severe Acute Respiratory Syndrome
SDK: Software Development Kit
SEM: Standard Error of the Mean
SR: Systematic Review
WC: Week Commencing

Statement of Original Authorship

This thesis's content has never been submitted to fulfill the requirements for a degree at this or another higher education institution. Except where appropriate reference is made, the thesis does not, to the best of my knowledge and belief, contain any previously published or written work by another author.

Signature: _________________________

Date: _________________________

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Thank you all for being a part of this remarkable journey.

Taha Hatcha

Chapter 1: Introduction

In a world fueled by digitalization, the abundance of daily-generated data holds immense potential for enhancing decision-making, urban planning, and the creation of sustainable and livable cities. However, a substantial portion of this precious data remains untapped, lurking in the digital shadows, and consequently, cities miss opportunities for more efficient and effective governance. This research attempts to harness the potential of MaaS data to develop an innovative approach that extracts meaningful insights from urban data, focusing on the synergy between MaaS and city planning.

Within the dynamic landscape of urban planning, the use of urban mobility data offers a unique avenue for the formulation of more informed and pragmatic strategies. This dissertation endeavors to explore this frontier, driven by the vast possibilities unlocked by advanced AI data analysis techniques, particularly NLP. At its core, this research seeks to unravel the nature of MaaS data, shedding light on its essential attributes and its significance within the broader realm of urban planning.

With a focused purpose, this study sets out to gather and analyze data from a spectrum of 200 global MaaS organizations, delving into their organizational structures. The goal extends beyond data aggregation; it delves into the subtle complexities behind the MaaS system, attempting to generate insights to enhance the usability of MaaS data for city planning.

Grounded in a systematic review approach using the PRISMA framework, the literature review conducted within this research intends to shed light on the latest developments and advancements in the field of MaaS, thereby paving the way for a more profound exploration. Furthermore, a dedicated segment of this dissertation is dedicated to unraveling the profound impact of the global pandemic on the MaaS. This involves tracing the contours of urban mobility's "new normal," capturing the challenges, adaptations, and unprecedented opportunities that have emerged as a result.

1.1 BACKGROUND

In the context of contemporary urban planning, the utilization of modern urban mobility data has garnered increasing attention as a means to address the complex challenges posed by evolving transportation dynamics (Karimi et al., 2021). Traditional urban mobility frameworks often struggle to comprehensively capture the complicated interplay between diverse transportation modes, user behaviors, and real-time trends that characterize modern urban mobility (Sarasini et al., 2017). This inadequacy underlines the need for innovative approaches that harness the potential of advanced data analysis tools.

The evolving landscape of urban mobility is significantly influenced by technological advancements, changing consumer preferences, and shifting patterns of urbanization (Jeyaseelan et al., 2022). Against this backdrop, MaaS presents a promising concept, offering integrated and sustainable transportation solutions that have the potential to reshape urban mobility paradigms (Arias & C., 2020). However, to better realize the benefits of MaaS, an overall understanding of its data nature, features, and contextual relevance is essential. This research seeks to bridge this knowledge gap by presenting the multifaceted structure of MaaS data to enable better-informed decision-making in urban planning.

Furthermore, the global pandemic has underscored the need for adaptable and resilient urban mobility systems (Linares & G., 2021). The disruption caused by the pandemic has highlighted the importance of understanding the interplay between MaaS and such forceful events, which can significantly influence mobility patterns and preferences. Therefore, an exploration of the pandemic implications on MaaS adds a layer of significance to this research.

In summary, this research is grounded in recognition of the limitations of traditional urban mobility frameworks, the significant potential of MaaS, and the need to harness advanced AI data analysis tools for a more comprehensive understanding of urban mobility dynamics. The background of evolving technological, societal, and environmental factors further emphasizes the timeliness and relevance of this study in contributing to the advancement of urban planning strategies.

1.2 CONTEXT

This study unfolds within the dynamic and intricate context of contemporary urban planning, where the interplay of a range of factors shapes the mobility landscape of modern cities (Machado et al., 2018). Urbanization, technological innovations, changing users' behavior, and the recent challenges posed by global events like the pandemic collectively emphasize the need for innovative approaches in urban mobility management.

Traditional urban transportation systems, often structured around single modes of travel, now face limitations in meeting the diverse and evolving mobility needs of urban populations (Daniela et al., 2022). As cities become more densely populated and interconnected, the demand for efficient, sustainable, and seamless transportation solutions has intensified. In response, MaaS has emerged as a remarkable step toward change in the urban mobility planning field (Krauss et al., 2022). MaaS envisions a paradigm shift by integrating multiple modes of transportation into a cohesive and user-centric system (Pagoni et al., 2022). It promises to enhance the efficiency of urban mobility, reduce congestion, decrease emissions, and ultimately improve the quality of life for city dwellers (Esztergár & K., 2020).

Furthermore, the global pandemic has significantly disrupted urban mobility patterns and posed unprecedented challenges to city planners (Zeidan et al., 2022). The context of the pandemic highlights the urgency of understanding how external shocks, such as public health crises, influence mobility preferences and behaviors. From this perspective, examining how the pandemic has affected MaaS takes on greater importance as it offers insights into how well MaaS systems can adapt and withstand crises.

In summary, this study evolves within a circumstance where traditional urban mobility systems are strained, and the potential for integrating MaaS in the process of modern urban planning is disposed for exploration. The evolving urban landscape, coupled with the pressing need for adaptable and resilient mobility solutions, gives depth and urgency to this research.

1.3 OBJECTIVES

This study serves multiple interconnected purposes that collectively contribute to a better understanding of the MaaS dynamics and refining city planning strategies:

1. **Understanding MaaS Organization Features**: Investigate and identify the essential characteristics of MaaS organizations to enhance their integration into the city system. This involves exploring key attributes for more effective implementation and utilization. The primary objective here is to gain insights into what makes MaaS organizations impulse, work more seamlessly, and pave the way for smoother incorporation to benefit urban planning.

2. **Comprehensive Exploration of MaaS Data:** Conduct an in-depth exploration of the MaaS ecosystem, including its data types, while providing clear definitions. Additionally, an alignment with SDGs and their associated objectives to identify and analyze practical use cases of MaaS data in city planning.
3. **Understanding the MaaS-Pandemic Nexus**: Investigate the mutual influence between the COVID-19 pandemic and MaaS. This research aims to discern how the pandemic affected the mobility of people and MaaS and, conversely, how MaaS may have impacted the spread of the pandemic.

1.4 SIGNIFICANCE

Within the context of this dissertation, the significance of the study echoes through various dimensions, attempting to advance urban planning knowledge and practice through the following:

- The exploration into MaaS data's particulars serves as a cornerstone in enriching the comprehension of the new urban mobility dynamics. By dissecting the nature and characteristics of MaaS data, this study tries to lay a foundation upon which urban planning decisions can be grounded. This, in turn, can facilitate more informed and effective strategies that cater to the diverse and evolving mobility needs of modern cities.
- The integration of advanced AI data analysis tools carries the promise of revolutionizing urban planning methodologies. Through the extraction of insights from MaaS data, urban planners are empowered to craft strategies that align with urban development goals. The implications can be far-reaching, extending to improved transportation systems, reduced congestion, enhanced sustainability, and heightened overall quality of urban life.
- The study's exploration into how the global pandemic has affected MaaS resonates with significant real-world implications. By analyzing the pandemic's effects on mobility patterns, this research has the potential to contribute to the design and implementation of adaptable and resilient mobility systems. These insights can equip urban planners and policymakers with the tools to navigate unexpected disruptions effectively and ensure the continuous functioning of urban mobility networks.

- By delving into the particulars of MaaS components, stakeholders, and data types, the study fosters collaboration among the diverse actors within the urban mobility ecosystem. This cooperative approach is crucial for jointly creating comprehensive and efficient transportation systems that are customized to meet the diverse needs of urban populations.
- Through the confluence of AI-driven analysis and MaaS data insights, the study envisions a future where urban planning transcends conventional boundaries. The integration of NLP-based tools empowers urban planners to derive actionable insights from data, facilitating anticipatory and timely responsive urban planning strategies.

In essence, the significance of this study resonates deeply with its prospective contributions to advancing urban mobility knowledge, fostering informed urban planning decision-making, assisting in building resilience against disruptions, promoting stakeholder collaboration, and envisioning future urban landscapes characterized by innovation and sustainability.

1.5 RESEARCH QUESTIONS

The research questions in this study are essential for understanding MaaS data's impact on urban planning.

1. How does a comprehensive exploration of MaaS data contribute to a deeper understanding of its nature, characteristics, and contextual relevance within the broader urban mobility landscape?
2. To what extent can the integration of advanced AI data analysis tools, specifically NLP, enhance the extraction of actionable insights from MaaS data, thus informing more effective and informed urban planning strategies?
3. What are the apparent effects of external disruptions, such as the pandemic, on urban mobility patterns within the MaaS framework?
4. What insights can be garnered from exploring MaaS ecosystem components and data types, and how can these insights facilitate collaboration among diverse urban mobility stakeholders to foster the creation of holistic and efficient urban systems?

Through thorough investigation and analysis, the research questions will be addressed, culminating in a better understanding of the features of MaaS data and its implications for urban planning.

1.6 HYPOTHESES

The hypotheses outlined in this research framework underpin a multifaceted exploration into the landscape of MaaS data and its implications for urban planning. Three hypotheses are formulated:

Hypothesis 1: Factors Influencing MaaS Integration

The higher the integration level of MaaS organizations within the urban system, the more likely they are to exhibit characteristics such as being public entities rather than private, having a longer history of operation, and incorporating a greater number of mobility modes. The following hypotheses interpret these factors:

- ✓ Hypothesis 1.1: Comparative Analysis of MaaS Integration Levels (Private vs. Public). Null Hypothesis (H_0): There is no significant difference in the mean integration levels between private and public MaaS companies. Alternative Hypothesis (H_1) indicates that there is a significant difference in the mean integration levels between private and public MaaS companies.
- ✓ Hypothesis 1.2: Relationship Between Years Since Creation and Integration Level: Null Hypothesis (H_0): There is no significant association between the number of years since the creation of a MaaS company and its integration level. Alternative Hypothesis (H_1): There is a significant relationship between the number of years since creation and integration level.
- ✓ Hypothesis 1.3: Relationship Between Integration Level and Number of Mobility Modes. Null Hypothesis (H_0): There is no relationship between the integration level of MaaS companies and the number of mobility modes they offer. Alternative Hypothesis (H_1): There is a relationship between integration level and the number of mobility modes.

Hypothesis 2: deriving actionable insights for urban planning from MaaS data.

In this hypothesis, the aim is to investigate whether MaaS data can offer practical insights and concrete use cases that contribute to urban sustainability and the achievement of SDGs. This hypothesis forms a critical aspect of this study, as it seeks to unravel the extent to which MaaS data can play a role in fostering sustainable urban development.

The null hypothesis suggests that there is no meaningful connection between MaaS data and SDGs, while the alternative hypothesis posits that such a connection exists. The study aims to test whether MaaS data can indeed support urban sustainability and SDGs by exploring the insights generated from the data analysis and their relevance to achieving sustainability goals in cities.

Null Hypothesis (H_0): There is no significant relationship between MaaS data and their alignment with SDGs. In other words, MaaS data do not provide meaningful insights that support urban sustainability and SDGs.

Alternative Hypothesis (H_1): There is a significant relationship between MaaS data and their alignment with SDGs. Specifically, MaaS data can provide essential perceptions and generate use cases that contribute to urban sustainability and help achieve SDGs.

Hypothesis 3: Adaptation in response to external disruptions

The hypothesis suggests that external disruptions, such as the global pandemic, significantly impact urban mobility patterns. Understanding these effects is vital because it prompts the development of flexible and robust mobility systems. Such adaptability ensures that urban mobility remains efficient despite unexpected disruptions. The hypothesis proposes that integrating MaaS and advanced mobility systems could enhance urban resilience by minimizing person-to-person contact. It aims to explore whether the adoption of MaaS can help cities become more resilient and sustain their urban patterns.

In essence, the hypothesis suggests that MaaS integration could mitigate the adverse effects of disruptions like pandemics by offering alternative and safer mobility options, which can enhance the city's ability to cope with and recover from unexpected events while maintaining functional urban mobility systems.

Null Hypothesis (H_0): There is no significant improvement in urban resilience attributed to the implementation of MaaS and advanced mobility systems.

Alternative Hypothesis (H_1): The deployment of MaaS and advanced mobility systems significantly enhances urban resilience, resulting in more effective responses to pandemics.

Through the following chapters, this research will attempt to provide empirical evidence supporting the hypotheses and clarify the sophisticated nature of MaaS data, its ability to improve decision-making, and the necessary adaptability in the face of disruptions.

1.7 THESIS OUTLINE

This thesis follows a structured framework comprising seven chapters: The introduction lays the groundwork, emphasizing the importance of MaaS data in urban planning. The literature review provides theoretical context, while the research design chapter details the methodology. Data analysis explains data collection and NLP techniques, and the results chapter presents findings. The discussion contextualizes these results within existing research, and the conclusion summarizes key insights and outlines future directions, see Fig. 1. This organization ensures a systematic exploration of MaaS data's role in urban planning.

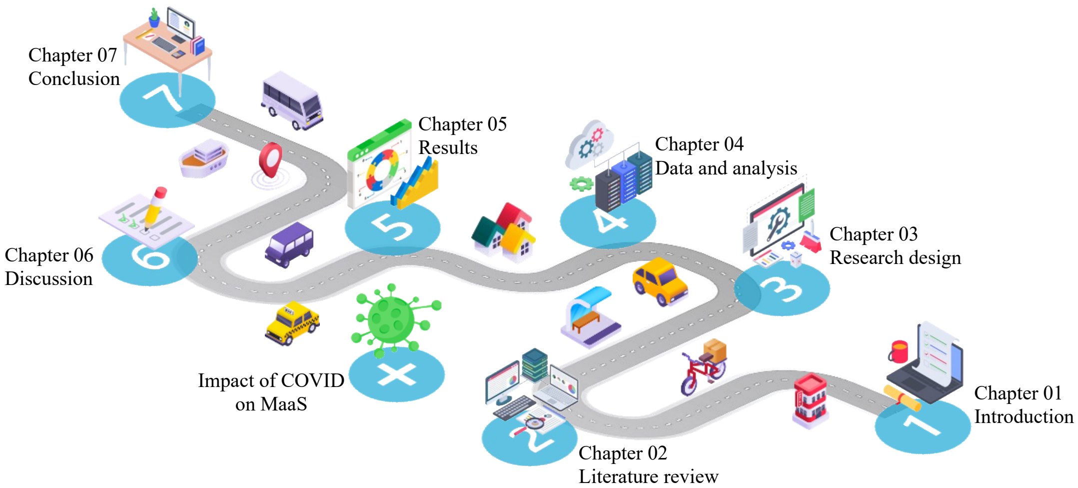

Fig. 1. Research Plan. Source: The Author

The present study starts by explaining the research subject, purpose, and significance, as well as the methodology and the findings of the study. Chapter 1: offers a comprehensive overview of the background information that underpins the research. It delineates the research question and highlights the purpose and significance of the study. Moreover, it defines the key concepts that are integral to the research. Chapter 2: situates the forthcoming study within the context of existing theoretical paradigms. Drawing on pertinent studies, this chapter delves into the prominent themes and concepts that underpin the MaaS. It explores the theoretical and empirical foundations of the research, thereby situating it within the broader academic landscape. Explicates the reasoning and validation for the research methodology choices. It places a particular focus on the scope of the study and the methods that are employed to achieve the outlined objectives. This chapter presents an in-depth analysis of the research design, sampling techniques, data collection, and data analysis tools.

Focuses on data collection, the MaaS ecosystem, the definition of data types, and the use of NLP and data processing tools. This chapter explains the data sources, variables, and indicators used in the study. Moreover, it delineates the NLP and data processing tools employed for the analysis to achieve the research objectives. Presents the results of the research analysis and discusses the findings. It provides an in-depth analysis of the data and the patterns that emerged from the analysis. This chapter illuminates the key arguments, trends, and insights gleaned from the study. Chapter 6: discusses the results and compares them with similar approaches in the literature. It situates the findings within the broader academic discourse and elucidates their significance in the field.

Chapter 7: offers a conclusion to the study. It starts with evaluating the hypothesis outlined at the beginning of the study and then provides a summary of the key findings and insights that emerged from the investigation. Moreover, it delineates the limitations of the study and offers avenues for future research. This chapter underscores the significance of the study for policymakers, practitioners, and researchers in the field of urban planning and MaaS.

The Excursive Chapter: Impact of COVID on MaaS delineates the influence of the pandemic on urban mobility, with a specific focus on MaaS. It investigates how the pandemic has affected the demand for urban mobility and its related services, but the primary goal is to reveal the impact that MaaS systems can have during severe disruptive events like the pandemic. This chapter elucidates the difficulties that arose during the pandemic and how MaaS has influenced them.

Fig. 2 depicts the structure of the thesis, emphasizing the interdependence and collaboration among each component as they collectively contribute to constructing the primary framework of the research plan.

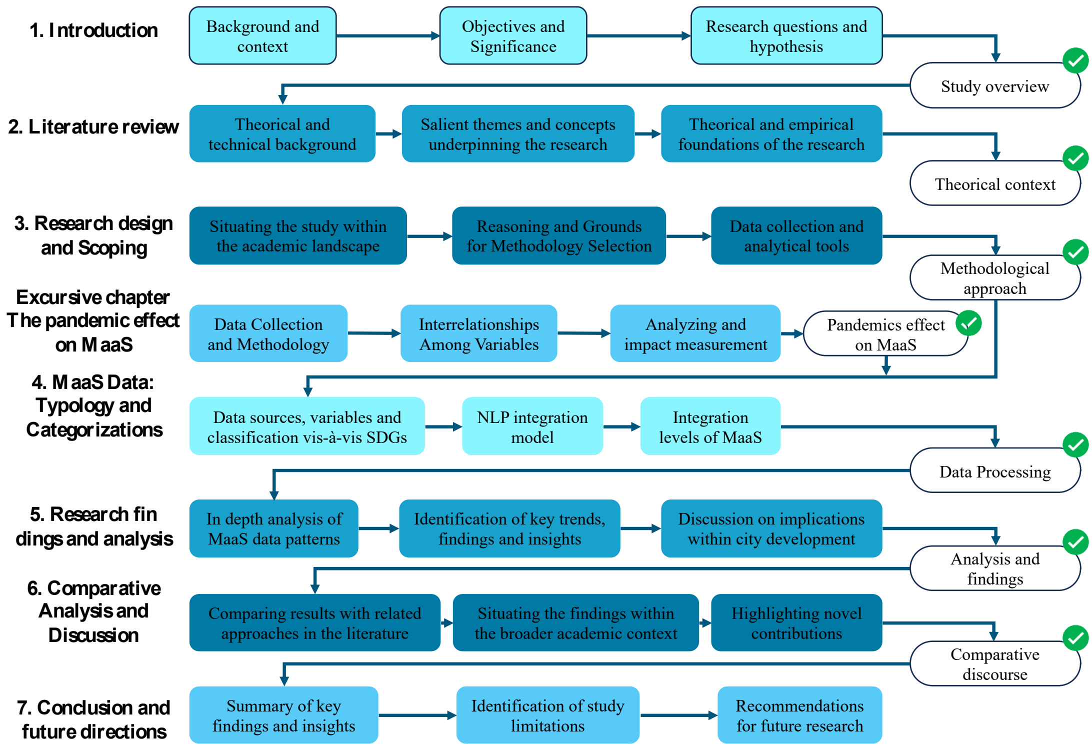

Fig. 2. Thesis Outline. Source: The Author.

Overall, the thesis covers three important aspects of MaaS. Firstly, it aims to understand what makes MaaS organizations effective in city planning, aiming to help cities integrate them smoothly. Secondly, it explores the different types of data used in MaaS and how they can be used for city planning, aligning them with sustainability goals. Lastly, it investigates how the COVID-19 pandemic has affected MaaS and vice versa, studying changes in how people move around and how MaaS might have influenced the spread of the virus. This research's **main objective** is to help cities better understand and use MaaS to improve urban mobility and planning for the future.

This research sets out to explore four **main questions** about MaaS data and its relevance to urban planning. First, it looks at how examining MaaS data can help to better understand its characteristics and importance in urban mobility. Second, it investigates whether using advanced AI tools like NLP can be useful in extracting insights from MaaS data to improve urban planning. Third, it examines how external disruptions like the pandemic affect urban mobility patterns within the MaaS system. Lastly, it explores how studying MaaS ecosystem components and data types can promote collaboration among different urban mobility stakeholders.

The study introduces three **hypotheses** regarding MaaS integration, data utilization for urban planning, and adaptation to external disruptions. Hypothesis 1 suggests that MaaS organizations integrated into urban systems are more likely to exhibit characteristics such as public ownership, longer operational history, and a diverse range of mobility modes. Hypothesis 2 aims to determine if MaaS data can provide actionable insights for urban sustainability and SDGs. Lastly, Hypothesis 3 explores the role of MaaS in fostering urban resilience, particularly in response to external disruptions like the global pandemic, by investigating its potential to bolster adaptability and resilience in urban mobility systems.

Chapter 2: Literature Review

The academic literature about the evaluation of contemporary urban mobility data and the emergence of novel mobility trends has experienced significant growth in recent years (Bibri, 2021). This expansion has originated from various academic disciplines, posing challenges for researchers to effectively monitor its evolving progress (Pons-Prats et al., 2022). This chapter extensively explores pertinent literature, encompassing diverse topics within the established thematic framework.

The first part, section 2.1, provides a clear explanation of the MaaS concept from the city planning perspective by highlighting its benefits and advantages over the conventional mobility system. It also involves examining existing literature on MaaS to identify research gaps and acquire a clear picture of the current state of the art. The study utilizes a Systematic Review (SR) approach, which involves a rigorous and methodical process for identifying, selecting, and evaluating relevant studies to be included in the review. This process aims to minimize potential bias and enhance the credibility and accuracy of the review's findings (Page et al., 2021). Thus, the designated SR method is PRISMA, conducted in section 2.2. To acquire a deeper understanding of the practical functioning of MaaS and to explore its evolution and position within the broader mobility industry, section 2.3 reports the technological advancements and market expansion aspects of MaaS.

To comprehensively harness MaaS data for city planning, a review of urban data processing tools is essential. With NLP emerging as a dynamic solution to decipher heavy text data, section 2.4 presents related approaches and their applicability and capabilities compared to NLP in the scope of this study. Section 2.5 further examines the literature on NLP for urban planning and its implications. In section 2.6, the repercussions of the pandemic on urban mobility are presented. This exploration aims to provide a broader understanding of the intersection between COVID-19 and MaaS and will be developed further in the excursive chapter at the end of this thesis.

2.1 MAAS CONCEPT

Although the term MaaS began to gain substantial recognition recently, the idea behind it has existed for a while. The ENTER Conference in Innsbruck, Austria, in 1996 introduced a corresponding notion to MaaS (Tschanz & Z., 1996) with the purpose of incorporating travel services into a hi-tech platform.

MaaS is generally portrayed as an innovative, promising strategy for restructuring mobility in a convenient way for the user to minimize the ownership of automobiles (Arias & C., 2020). The primary goal of MaaS is to place customers at the center of transportation services by providing them with specialized mobility alternatives according to their individual preferences and specific requirements (MAAS-Alliance, 2022). This implies that, for the inaugural time, the user will have easy access to the proper mobility modes or services as part of a range of flexible travel service offerings, see Fig. 3.

Many academic works have highlighted the importance of MaaS. As people move away from owning vehicles and prefer pay-per-use mobility, MaaS is becoming a significant new economic model. It has the potential to change how people travel and view urban mobility (Karlsson et al., 2020).

2.1.1 MaaS advantages

As demonstrated in Fig. 3, the benefits of implementing MaaS systems over conventional mobility systems can be observed. In the conventional mobility system on the right side, the user is compelled to utilize different modes of payment for various mobility options, resulting in a disjointed and fragmented mobility experience. This approach impedes accessibility and harmonization within the mobility system and creates complications for the user. Conversely, the MaaS system, depicted on the left-hand side, provides the user with a single, comprehensive access point to all mobility modes. This streamlined approach fosters ease of use and facilitates seamless access to mobility options.

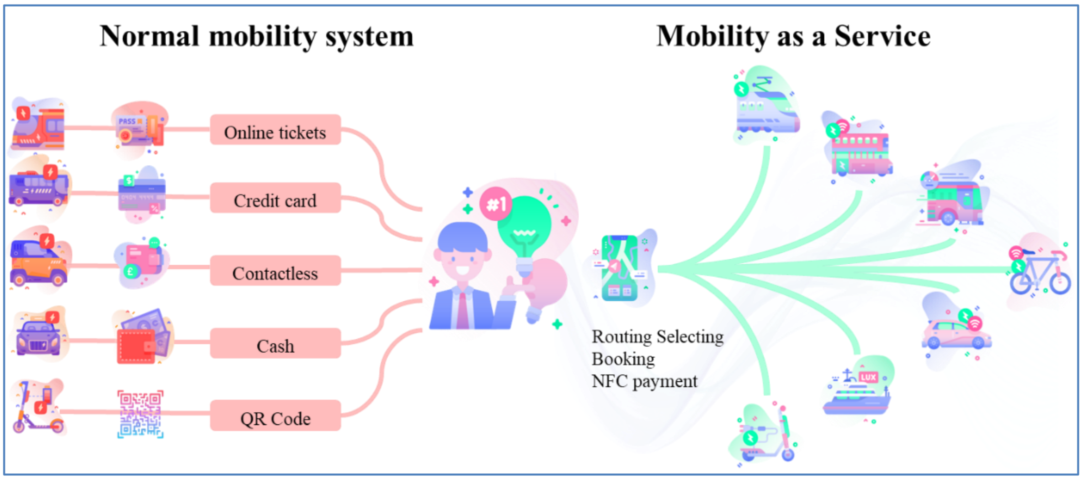

Fig. 3. The Combination of Multiple Transportation Options into a Single Digital Mobility Solution. Source: The Author.

Unlike conventional mobility systems that primarily rely on the utilization of privately owned vehicles, MaaS is intended to pivot towards the end-user and their experience of mobility rather than the transportation mode itself (Nikitas et al., 2017). Its ultimate goal is to provide the user with a seamless and customized mobility experience (Pagoni et al., 2022). Furthermore, the traditional mobility systems demonstrate some limitations that are addressed by MaaS. The significant ones can be summarized as follows:

- Lack of integration and coordination between different modes of transportation: the distinct transportation modes of the traditional PT systems are often managed by distinct agencies or companies, with minimal collaboration or integration among them. As a result, planning and executing trips involving various transportation modes can be challenging for users (Esztergár & K., 2020). On the other hand, MaaS systems are specifically designed to present a cohesive and unified experience for users, with a centralized location offering all the pertinent information and services.
- Limited accessibility and flexibility: Traditional public transportation systems frequently adhere to predetermined schedules and routes, resulting in complications for individuals with mobility impairments or those requiring transportation at atypical hours. In contrast, MaaS systems are intended to exhibit greater flexibility and adjustability (Musolino et al., 2022), accommodating the diverse requirements of users. These systems present a range of options to optimize the mobility experience, including on-demand services and tailored suggestions.
- Poor user experience: The public transport experience may be associated with negative feelings, such as discomfort and inconvenience, particularly during peak hours or in areas with high congestion or insufficient infrastructure (Aidoo et al., 2013). Furthermore, factors such as delays, overcrowding, and inadequate maintenance may contribute to a perception of unreliability among users (Chatterjee et al., 2020). Consequently, this may dissuade numerous users from utilizing these systems, particularly those who possess alternate means of transportation at their disposal. MaaS systems, on the other hand, are designed to provide a better user experience, with a greater focus on convenience, personalization, and customer service (Ho et al., 2021).

- Limited use of technology and data: Traditional PT systems often lack the technology and data infrastructure needed to provide real-time information, personalized recommendations, and other services that can enhance the user experience. In contrast, MaaS systems rely heavily on technology and data to provide users with the information and services they need (Shang et al., 2022).

In summary, the primary drawbacks of traditional public transportation systems compared to MaaS pertain to their deficiency in integration, adaptability, and user-centricity. MaaS systems are tailored to eliminate these limitations and provide users with a more convenient, versatile, and personalized mobility experience.

Thus, the MaaS concept indeed advocates a paradigm change in urban mobility by fusing new forms of mobility with established services; PT aims to improve the frequency and availability of transportation options, thereby increasing access to mobility services for a larger population. Additionally, MaaS can potentially reduce the number of private cars on the road, which in turn can lower the need for cities to expand their transportation networks. As a result, MaaS can contribute towards reducing pollution, traffic congestion, and emissions of harmful gases such as carbon dioxide and nitrogen dioxide.

Considering the significant advantages that MaaS offers, incorporating local strategies into international projects becomes essential. The United Nations' SDGs aim to create cities that are inclusive, safe, resilient, and sustainable (Timothy Kellison, 2022). MaaS can play a significant role in achieving these objectives by facilitating better planning practices, optimizing vehicle utilization, providing seamless digital access, and improving fleet management. Therefore, implementing MaaS initiatives is assumed to be a good step towards fulfilling the SDGs' objectives.

2.1.2 MaaS concept in the literature

Given the rapid and extensive growth of the MaaS concept, it is essential to provide a comprehensive overview of the topic and its reception across various academic disciplines. The earlier MaaS reviews have been conducted primarily to provide comprehensive explanations of the term's definition and scope (Soehartono & Khor, 2020). Some of the previous reviews on MaaS have also highlighted the difficulties and obstacles encountered in implementing and deploying such systems (Mulley, 2017), along with outlining the fundamental requirements necessary for their successful implementation (Kamargianni et al., 2016). Nevertheless, the number of studies that examined bibliographies with an SR and meta-analysis is limited. For instance, Wittstock & Teuteberg (2019) attempted to determine the key components of MaaS by examining 95 documents, including 37 scientific papers. Utriainen & Pöllänen (2018) selected 31 publications to address the functions of transport modalities in MaaS. Durand et al. (2018) precisely analyzed the travel preferences and the behavior of MaaS users based on 14 research works. The most recent study examined 57 publications with an emphasis on MaaS, the majority of which were peer-reviewed articles (Arias & C, 2020).

Fig. 4. illustrates the number of publications on the topic of MaaS from 1997 to 2023. The data presented shows a clear trend of increasing publications in the scope of MaaS.

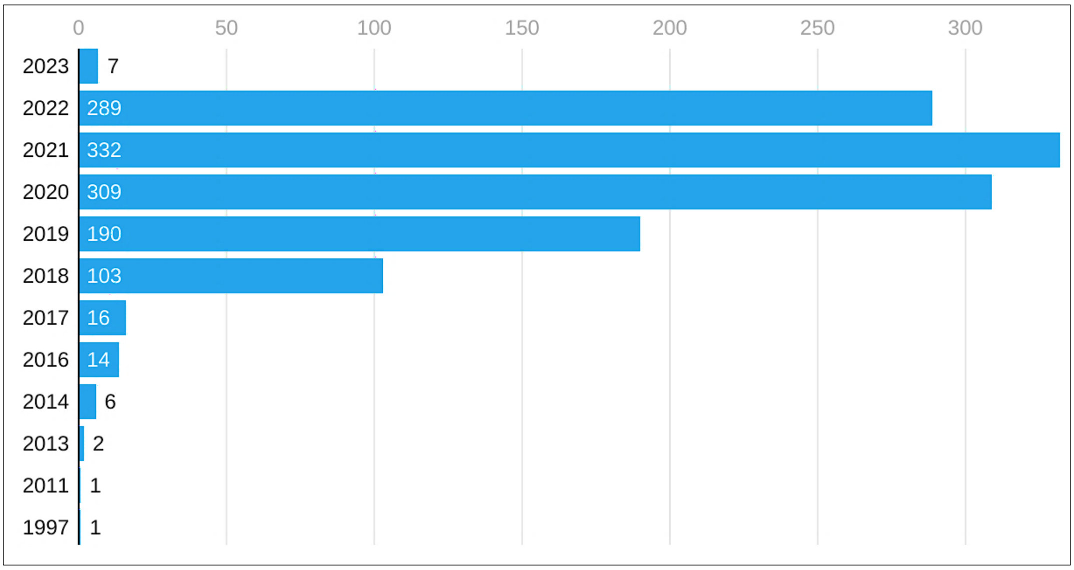

Fig. 4. Number of Publications in the Scope of MaaS since 1997. Source: The Author, 08.2022.

The first publication related to MaaS was recorded in 1997. However, more articles were only published in 2011 and 2013. The number of publications remained relatively low until 2016 when it increased rapidly. In 2018, the number of publications jumped significantly to 103; in 2019, it reached 190. In 2020, there was a substantial surge in publications to 309, indicating a growing interest in MaaS. The data also shows a continuation of this trend in 2021 and 2022, with 332 and 289 publications, respectively. The marginal decline observed in the number of MaaS-related publications is attributed to a shift in focus towards subtopics such as micro-mobility, Electric Vehicles (EV) fleet charging, and emerging shared mobility modalities. These publications may not explicitly mention the MaaS concept, thereby contributing to a reduction in the overall number of MaaS-focused literature. It is also important to note that the decrease in the number of publications to only seven in 2023 is related to the timeline of the analysis, which was conducted in August 2022. As such, the 2023 publication data were not yet available at the time of the study.

Generally, the trend of increasing publications related to MaaS indicates a growing interest in the topic among scholars and practitioners and highlights the potential for MaaS to play an increasingly key role in the future of transportation.

The surge in MaaS-related publications is also an indication of the multidisciplinary nature of this topic, as researchers and practitioners from a wide range of fields, including transportation engineering, urban planning, computer science, economics, and social sciences, are contributing to the literature (Martinčević et al., 2022) (Athanasopoulou et al., 2022).

Fig. 5. represents the diverse range of contexts in which MaaS has been explored. The analysis of scientific articles and publications on MaaS indicates that the topic has received significant attention in the field of transportation and related disciplines.

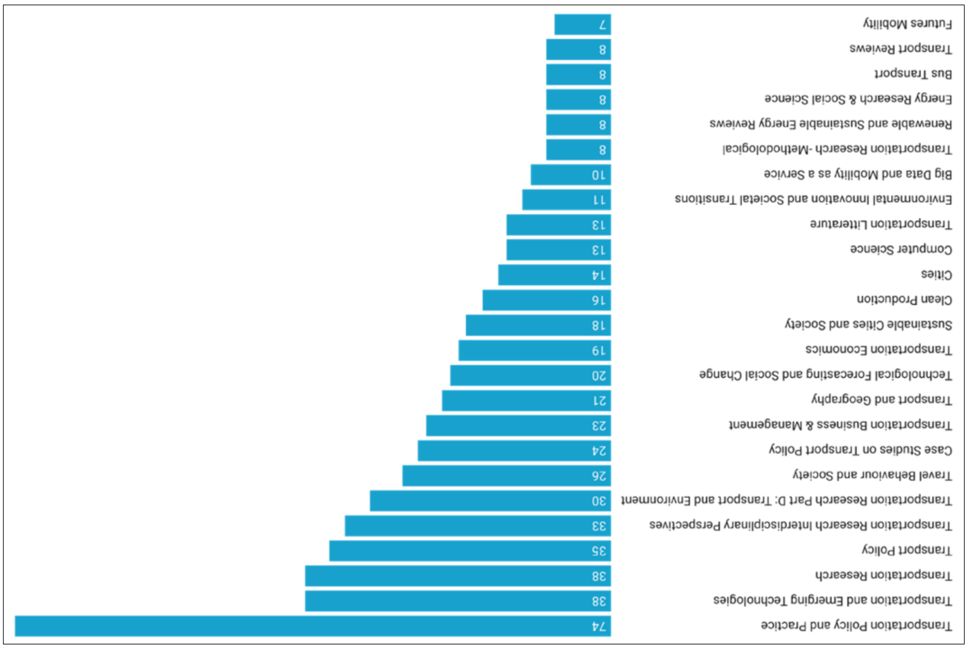

Fig. 5. Contexts and Counts of Literature Related to MaaS since 1997. Source: The Author, 08.2022.

The highest number of publications is in Transportation Policy and Practice (74), followed by Transportation and Emerging Technologies and Transportation Research (38 each) and Transport Policy (35). These results indicate that MaaS is a subject of interest across a broad range of transportation-related areas, including policy, technology, interdisciplinary research, and environmental considerations. The publication count in Cities (30) and Transport and Environment (30) indicates the relevance of MaaS in urban contexts and the significance of the environmental impact of transportation. The number of publications in Travel Behavior (26) and Case Studies on Transport Policy (24) suggests the attention given to how MaaS can influence travel patterns and the importance of examining specific cases for policy development.

Other notable areas with a substantial number of publications include Transportation Business & Management (23), which highlights the commercial aspect of MaaS, and Technological Forecasting and Social Change (20), which explores the impact of technological advancements and social changes on transportation systems. The presence of publications in Computer Science (13), Big Data, and MaaS (10) signifies the growing importance of technology and data analytics in the transportation field.

Indeed, the significant volume of publications on MaaS in diverse academic disciplines highlights its transformative potential in urban mobility and the growing interest in exploring its benefits and challenges. However, as the MaaS literature continues to expand, the task of comprehensively reviewing and identifying research gaps becomes increasingly challenging. In this regard, the present study has employed the PRISMA method to address this challenge effectively.

2.2 SYSTEMATIC REVIEW WITH PRISMA APPROACH

The SR involves a rigorous and exhaustive examination of all available research literature pertaining to a particular subject, followed by a meticulous evaluation and synthesis of the results (Green & Higgins, 2008). It aims to conduct a thorough analysis of the research findings from all the studies included in order to draw meaningful and conclusive inferences.

PRISMA guidelines aim to improve the transparency and completeness of reporting, enhance the reproducibility of the SR, and facilitate the assessment of the validity and reliability of the findings (Page et al., 2021). By following the PRISMA guidelines, researchers can ensure that their SR is conducted in a rigorous and transparent manner, which ultimately enhances the credibility and utility of the findings for future research and practice.

The identification and examination of the main review process, the sources, the number, and the outcome of each step specified in the PRISMA flowchart are uncomplicated. Fig. 6 syntheses the way registered records are managed throughout the review process.

It is imperative to include grey literature, such as official reports, statistical reports, white papers, and book chapters, to provide a comprehensive analysis of the research topic. These materials serve to broaden the perspective and enhance the depth of the literature review. However, it is noteworthy that peer-reviewed journal articles and conference proceedings remain the primary sources of information dominating the scholarly discourse for this research.

In August of 2022, the research was carried out, and subsequently, the results are delineated as the following:

1. The research keywords were specified as "Mobility as a Service" and "Data."
2. A total of 1,171 records were initially collected over an open timespan.
3. After narrowing the years of research to the period of 2013 to 2023, 863 results were obtained distributed as the following: 2023 (7), 2022 (271), 2021 (304), 2020 (281), 2019 (190), (103), 2017 (16), see Fig. 4.
4. Records registered: **779** results: review articles (30), research articles (639), book chapters (98), data articles (1), Editorials (11).
5. Records excluded: (Encyclopedia (46), Conference abstracts (1), Book reviews (2), Errata (2), Mini-reviews (2), short communications (5), and others (26).
6. Duplicated records and bibliographic data management were effectuated with the open-source reference management software Zotero[1]. The number of duplicated records was 157. Relevance detection of the retained items was double-checked- based on the research context via the AI tool Sysrev[2].
7. The number of records automatically removed was 151.
8. The number of records excluded due to irrelevance after screening was 583.
9. Reports sought for retrieval with n=196, of which 105 are not retrieved.
10. Reports assessed for eligibility n=91, 21 were removed. The reasons for excluding articles were mainly: reason (01) low-quality of data and analysis tools, reason (2) irrelevance to the main subject, reason (03) weakness or

[1] https://www.zotero.org/ (Last accessed on 02.2024)
[2] https://sysrev.com/ (Last accessed on 02.2024)

absence of the protocol designed, lack or absence of references, limited or incomplete evaluation methods, loss of quantitative data, repetitive publications, and language limitation.

The literature selection process resulted in 70 research items. The flowchart in Fig. 6 was developed using the online tool PRISMA flow diagram[3], following the PRISMA Statement and the reporting standards (Haddaway et al., 2022) based on the elaborated SR for this study.

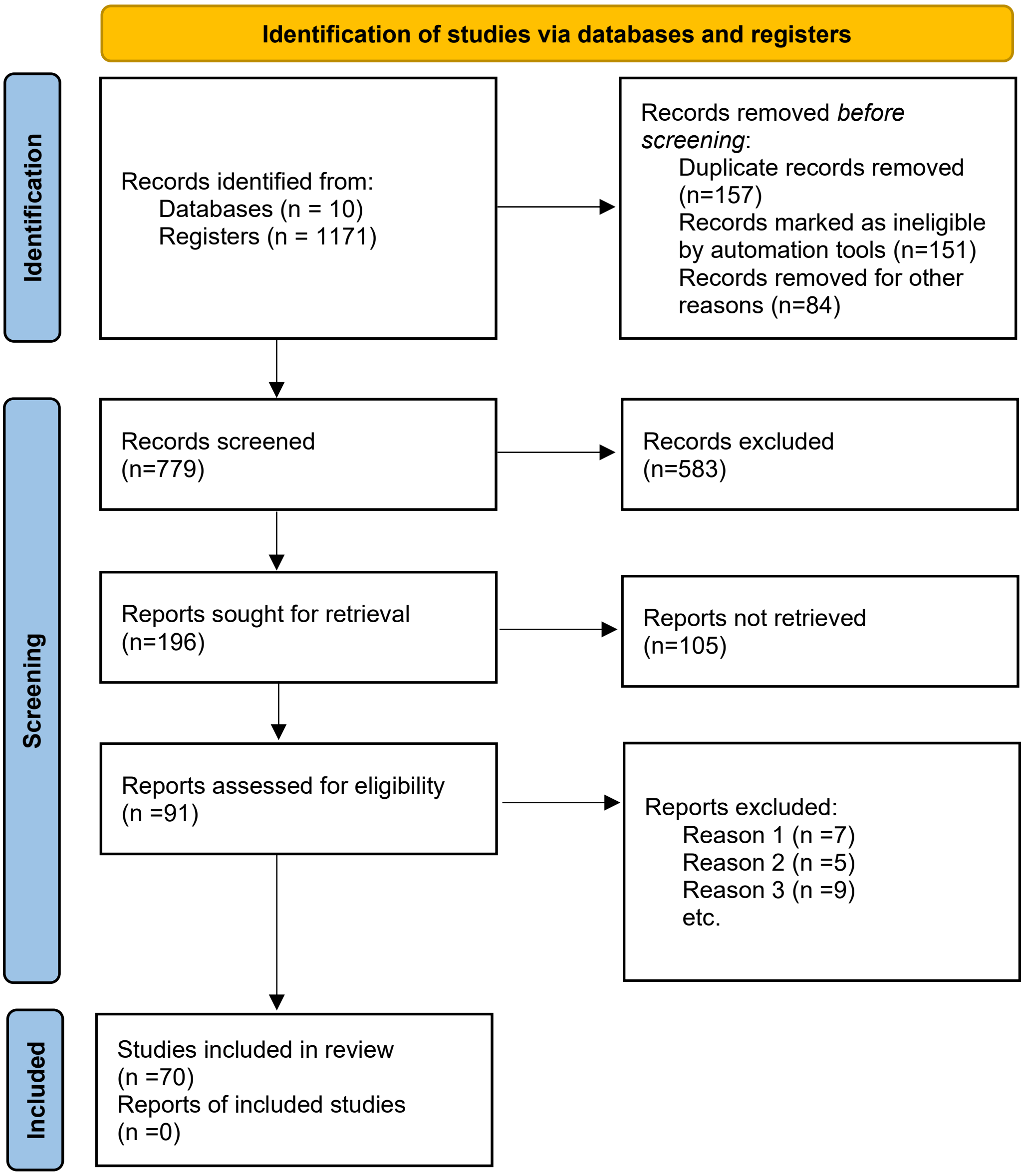

Fig. 6. PRISMA Flowchart for the Study Selection. Source: The Author.

[3] https://estech.shinyapps.io/prisma_flowdiagram/ (Last accessed on 02.2024)

The 70 designated documents are divided into five categories in 1)a)Appendix A. The categorization of research is contingent upon its methodological foundations to conceptual, theoretical, empirical, and case reports (Springer, 2022). The publications are presented in chronological order per year of publication. The number of theoretical articles is 16, while there are 23 conceptual and 17 empirical, and the number of case reports is 14. Each sort of article has a certain objective and has been evaluated using a diverse set of standards:

a) **Conceptual research papers** focus on the examination of a specific idea or concept. Typically, such papers entail conducting a thorough review of the extant literature on the topic of interest, followed by developing an original viewpoint or argument grounded in the gathered knowledge. These papers frequently serve as a building block for further research endeavors and are characterized by their emphasis on the integration of disparate concepts to suggest innovative connections between them. The value of conceptual papers lies in their capacity to construct coherent arguments rather than testing them empirically (Rocco et al., 2022).

b) **Theoretical research papers**, like conceptual research papers, aim to investigate and comprehend a specific notion or concept. However, theoretical research papers take a more in-depth look at the underlying theories and principles that support a particular concept and involve the development of new theoretical frameworks or models to better understand the topic (Ma et al., 2019). These papers are often used to explore complex or theoretical ideas containing new concepts that are connected to MaaS. Although peer-reviewed, these articles typically do not include experimental data.

c) **Empirical research papers**: report the results of studies that use empirical evidence to support their conclusions. Empirical evidence is information that is based on observation or experience rather than on theory (Bouter & Riet, 2021). In an empirical research paper, the authors conduct a study in which they collect data through experiments, surveys, or other research methods and analyze it to draw conclusions about the topic they are studying. Empirical research papers are meant to provide some perceptions of the workings of the natural world based on real data from MaaS pilots, who conduct experiments and examine the users' preferences, behaviors, and MaaS system features.

d) **Case report research papers** describe a specific instance or case of a particular phenomenon or condition. Case report papers are typically short, focused studies that provide detailed information to highlight unusual or interesting cases or to provide evidence to support a particular explanation or approach (Alpi & Evans, 2019). Case report research papers can provide more insights into the experiences of specific cases and help advance the understanding of different particularities and conditions.

2.2.1 Key Insights from MaaS Literature

The **conceptual studies** on MaaS cover a wide range of topics related to the concept and its implementation, including its definition and origins, opportunities and challenges (Hensher, 2017), the role of data in boosting the tourist experience (Cuomo et al., 2022), privacy concerns (Cottrill, 2020), barriers faced by transport authorities (Hasselwander & Bigotte, 2022), key stakeholders and modes of cooperation in the MaaS ecosystem (Hoveskog et al., 2022), development and implementation barriers (Ho et al., 2021), the use of an ecosystem approach to analyzing business models (Datson, 2016), factors that may limit the formation of MaaS (Meurs et al., 2020), latent demand for MaaS (Caiati et al., 2020), rhetoric and service model (Pangbourne et al., 2020), reliance on personal travel information (Cohen & Jones, 2020), technological advances (Wong et al., 2020), supply and demand sides of MaaS systems (Ho, 2022), considerations for vulnerable social groups (Dadashzadeh et al., 2022), economic, environmental, and social issues with car dependency (Knieling et al., 2020), principles for sustainability (Pritchard, 2022), and the two core strengths of the MaaS business model (Narupiti, 2019). Some studies also propose frameworks for designing and implementing MaaS bundles (Huang, 2022a)dc, present government-contracted models, quantify the net impact of MaaS, produce predictive models using ANN (Artificial Neural Network) analysis (Duan et al., 2022), examine operators joining MaaS platforms (Sakai, 2019), analyze literature and transport setting, and present a critical analysis of the rhetoric surrounding MaaS (AkshayVij, 2022).

The **theoretical studies** analyze the barriers to widespread adoption of MaaS (šulskytė, 2021) and the potential impacts on public transport use (Ho et al., 2020; Pizzi, 2021), while other articles propose methods for institutional integration (Gong et al., 2022) and explain how big data technology can be enabled for MaaS (Shang et al., 2022) (Bandeira et al., 2022). Some of the theoretical studies also review existing visualization technologies (Yang et al., 2022), highlight the barriers to MaaS adoption (Enoch, 2018), and present evidence of work in multi-disciplinary approaches for MaaS (Giesecke et al., 2016). Additionally, some studies propose a multidimensional system for evaluating and comparing MaaS schemes and describing the architecture behind a MaaS platform (Macedo et al., 2022). Another study aims to develop a MaaS Maturity Index to measure a city's readiness for the MaaS implementation (Kamargianni & Goulding, 2018). Finally, other studies explore the perceived enablers (Lyons et al., 2020), opportunities, barriers, and risks associated with using MaaS (Landolfi et al., 2019) and argue that MaaS is an evolutionary continuation in terms of transport integration (Bushell et al., 2022).

Based on the list of the selected articles, the main focus of the **empirical studies** is on understanding the potential market for MaaS (Ho et al., 2018) and examining the factors that influence its adoption and use (Casadó et al., 2020). Some of the studies investigate the mobility services that users are willing to pay for (Lopez-Carreiro et al., 2021) and the potential for changes in car use following a MaaS program (Sochor et al., 2015). Others present the results of exploratory MaaS pilot studies (Storme et al., 2020), explore the motivations and preferences of potential MaaS users (Tsouros et al., 2021), and assess the willingness to adopt MaaS based on several factors such as gender, age, education level, and occupation (E.-J. Kim et al., 2021). Some of the studies also discuss the barriers to acceptance and adoption of MaaS and the policies that address them and examine the potential for MaaS to replace private car ownership (Alonso-González et al., 2020). Additionally, some studies carry out a thorough analysis of the current European rules and policy framework (Matowicki et al., 2022) and investigate how people's lifestyles are associated with the MaaS acceptance (Pagoni et al., 2022). Finally, one of the studies looks at the features of MaaS platforms that influence user satisfaction levels across gender (Aman & Smith-Colin, 2022). The overall aim of these studies is to understand and evaluate the feasibility (Alyavina et al., 2020), potential (Mulley et al., 2020), and sustainability of MaaS offers as a transportation option by collecting and analyzing data from various sources and observations rather than carrying on a hypothetical structure in treating the topic (S. Kim & Rasouli, 2022).

The selected **case reports** on MaaS focus on specific contexts (Rantasila, 2015) and locations, such as Helsinki (Heikkilä, 2014), Hong Kong, Brisbane (Pickford & Chung, 2019), India (Singh, 2020a), and various European cities

(Musolino et al., 2022). They cover a range of topics related to MaaS, including its promotion as a flexible and efficient mode of transportation (E. Cooper & Vanoutrive, 2022), the key elements that support its adoption (Hasselwander et al., 2022), and its effects on land planning and mobility governance (Karlsson et al., 2016). The role of technology, such as Edge-Oriented Computing EOC and ML, in extending the reach of MaaS is also examined (Carvalho et al., 2019), along with the enablers and barriers to MaaS business models and the potential of MaaS Lite, an incremental approach to MaaS, in different contexts. The reasons for adoption (Geurs et al., 2018) and the impacts of MaaS on public transport use are also explored, as well as the main obstacles and enabling factors for the dissemination of MaaS platforms (Nikitas et al., 2017). The case studies also evaluate the potential of MaaS to reduce transport-related energy consumption and make rural places more accessible and livable and identify the major obstacles to the effective deployment of MaaS in developing countries (Kayikci & Kabadurmus, 2022). Finally, the case studies present the results of trials and tests of MaaS apps in various locations and offer trip-planning solutions.

At the conclusion of this chapter, research gaps will be summarized and identified, drawing from insights derived from the literature review presented in this section and subsequent sections. While the primary goal of this study is to uncover the data produced by MaaS and establish practical methods for its optimal utilization, it is crucial to complement that with an investigation into the technological attributes and evolution of the MaaS system. This facet of the study will be elaborated upon in the following section.

2.3 TECHNOLOGICAL DEVELOPMENT

Reviewing the technological advancements in MaaS is crucial for obtaining a thorough understanding of the present status and future potential of the MaaS system. This is important for recognizing possible opportunities and challenges that may arise during the implementation of MaaS. Examining the technological progress of MaaS aids in identifying deficiencies that need to be addressed and areas that warrant further research. Additionally, analyzing a number of MaaS companies can provide insights into the market demand for MaaS and help understand the complex interplay of technological, operational, and regulatory factors. This information supports predicting the future growth and development of MaaS and its potential impact on the urban realm.

2.3.1 The growth of the MaaS industry

Fig. 7 demonstrates the growth of the MaaS industry since 2007. The data is taken from the -MaaS corporations database of this research; see Appendix D. The figure shows a gradual increase in the number of companies involved. The establishment of the earliest MaaS companies in 2009 suggests that the concept of MaaS is relatively recent. The data indicates that there has been a significant increase in the number of MaaS companies, with a substantial surge in new companies founded in 2019 and 2020. This suggests that the MaaS industry is rapidly expanding and attracting attention. The data presents a broad range of MaaS companies, ranging from small startups to large established firms, indicating that there is substantial diversity and competition in the MaaS market. It also shows that the industry began with just three companies in 2007 and experienced remarkable growth over time, reaching its peak with 26 companies in 2017.

The growth of the MaaS industry is attributed to several factors, including technological advancements, shifting consumer preferences, and the need for more sustainable transportation options. The proliferation of smartphones and mobile apps has increased accessibility to MaaS platforms, resulting in a surge in adoption. Furthermore, consumers are seeking alternative transportation modes that are affordable, convenient, and eco-friendly, and MaaS provides a range of options to choose from, making it an attractive alternative to traditional modes of transportation.

The decline in the number of companies in the MaaS industry in 2020 and 2021 is due to several factors, including the impact of the COVID-19 pandemic on the transportation sector and the overall economic situation (He et al., 2020). The pandemic has significantly affected the transportation industry, with many countries implementing travel restrictions and lockdown measures, which resulted in reduced demand for transportation services (J. Kim et al., 2022). This decrease in demand for transportation services has negatively impacted the growth and sustainability of some MaaS companies, leading to closures or mergers. Moreover, the economic situation caused by the pandemic has made it difficult for some MaaS companies to secure funding, which has led to their closure. Additionally, some companies have shifted their focus to other sectors due to the uncertainty and challenges brought about by the pandemic. It is also important to note that the MaaS industry is relatively new and still evolving. The growth of new companies can be rapid, but the decline is also possible when some companies fail to keep up with the evolving technology and market trends.

In brief, the expansion of the MaaS sector throughout recent years signifies a growing desire for sustainable and integrated means of transportation. Despite its nascent stage, the MaaS industry presents numerous prospects. However, there is currently a dearth of scientific research on the progression and technological maturation of MaaS.

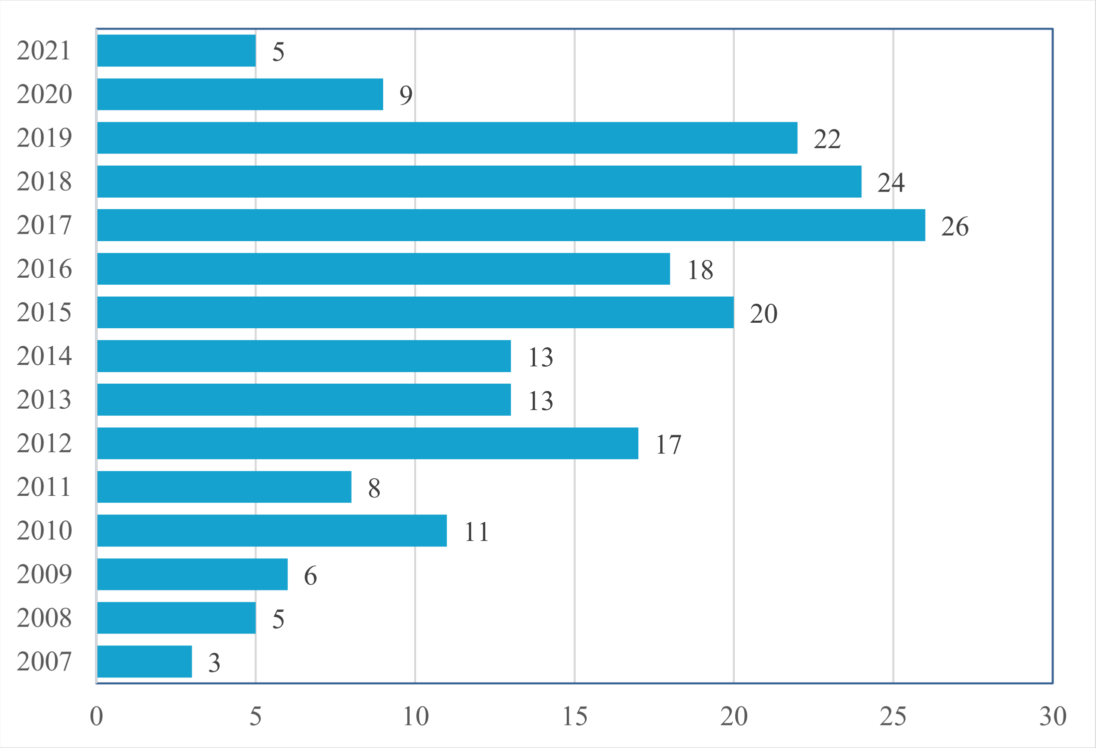

Fig. 7 Count of MaaS Corporations According to their Year of Creation from 2007 to 2023. Source: The Author.

2.3.2 MaaS Market growth

The growing popularity of MaaS is further driven by the emergence of smart cities and the adoption of the Internet of Things (IoT) technologies (Trindade et al., 2017). This has facilitated the collection and analysis of large volumes of data, which can be leveraged to develop predictive models and optimize transport systems (Parra-Domínguez et al., 2022). Thus, the growth of the MaaS market is attributed to the increasing demand for sustainable and convenient transportation options (Lazar et al., 2022), which has led to a shift towards shared mobility services. Also, advancements in technology have enabled the development of innovative business models that cater to different user needs and preferences (Silva et al., 2022).

The market for MaaS was estimated in 2021 at around $128,489.2 million. From 2021 to 2030, it is expected to grow at a Compound Annual Growth Rate (CAGR) of 16.8% (P&S Intelligence, 2022). The uptake of MaaS is expected to boost market growth, primarily driven by concerns about greenhouse gas emissions, urban traffic congestion challenges, the cost-effectiveness and accessibility of MaaS services, and heightened government support.

Moreover, it is expected that traffic congestion on roadways will deteriorate in the near future due to the rapid growth of emerging economies. Despite investments exceeding hundreds of billions of Euros in planning and expanding transport infrastructure, traffic congestion in metropolitan areas continued to increase by up to 144% (Rode et al., 2017). MaaS aims to efficiently utilize the existing public and private transportation infrastructure to help reduce traffic congestion.

2.3.3 MaaS Market segmentations

Reviewing the MaaS market segmentations holds significant value in investigating the utilization of MaaS data in urban development planning for multiple reasons:

- Firstly, it enables the identification of various MaaS providers, their intended audience, and their business strategies, which is essential in understanding the diverse sources of MaaS data and the reasons why MaaS providers share their data (Becker et al., 2020).
- Secondly, dividing the MaaS market allows for a better understanding of the diverse types of MaaS users and their travel behaviors (Stopka et al., 2018). By doing so, the data analysis and modeling can be customized to different user segments, leading to more accurate insights to be applied in city planning.
- Lastly, inspecting the MaaS market's segments helps to recognize the various forms of MaaS data, as well as their strengths and limitations. This information is crucial in developing data-driven tools and models for city planning.

The literature review identified several academic works that provided insights into MaaS market segmentation and its implications for city planning. Heikkilä et al. (2018) provided an overview of different MaaS business models and value propositions. The authors identified several types of MaaS providers, such as aggregator, operator, and platform providers, and discussed their target markets and business strategies. Tsivgoulis et al. (2019) conducted a critical review of MaaS definitions, assessments of schemes, and key challenges. The authors highlighted the importance of understanding the various MaaS segments and user needs for the successful implementation of MaaS services. Anable et al. (2019) investigated the potential impact of MaaS on active travel, highlighting the need for MaaS services to encourage sustainable modes of transportation. Tang et al. (2020) conducted a case study of Gothenburg to identify user groups and travel patterns for MaaS services. The authors found that different user segments had different travel patterns and needs, which could inform the development of MaaS services tailored to specific user groups. Kamargianni et al. (2020) conducted a survey in four European cities to segment MaaS users based on their travel behavior and attitudes. The authors identified four user segments: "traditional public transport users," "car drivers," "active sustainable transport users," and "diverse transport users. Rashidi et al. (2020) reviewed the literature on MaaS and its potential impact on public transport, highlighting the need for further research on the impact of MaaS on transit ridership and revenue. Finally, Kattan et al. (2021) conducted a critical review of the literature on MaaS and identified several research gaps, including the need for more research on MaaS market segmentation and user needs. The authors recommended that future research should focus on the development of MaaS services that are tailored to specific user needs and travel patterns.

By understanding the different MaaS providers, users, and data sources, a more nuanced and comprehensive understanding of the challenges and opportunities presented by MaaS can be developed. In section 4.4, this study will focus extensively on MaaS operators, their services, and the overall elements of the ecosystem.

2.4 EVALUATION OF RELATED DATA PROCESSING APPROACHES

With the increasing availability of data, it is essential to choose the proper tools and approaches that can handle the complexities of urban data. Furthermore, the need for a new generation of scientific instruments and procedures has become increasingly important due to the pace and scale of data production. Traditional data analysis techniques that rely on a recognizable tabular format are no longer adequate to handle the vast amounts of unstructured data generated by cities (Gandomi & Haider, 2015).

Therefore, NLP offers a unique advantage by enabling researchers to uncover nuanced patterns, features, and contextual information embedded within a vast array of text-based resources (Zulkarnain & Putri, 2021). In the context of urban mobility data, where information is often scattered across social media posts, online reviews, news articles, and user-generated content, NLP techniques excel at deciphering public sentiments, identifying emerging trends, and extracting actionable intelligence (Tikhonova et al., 2022). By harnessing the power of NLP, researchers can unlock a deeper understanding of urban mobility challenges, preferences, and behaviors, facilitating more informed policy decisions, targeted interventions, and innovative transportation solutions that are attuned to the intricate fabric of urban life.

However, in this section, other methods related to the research objectives and comparable to NLP are presented and delineated in alignment with the research objectives, as well as their relevance and applicability. The key features of the approaches are summarized in Table 1.

2.4.1 Cloud Natural Language

A service provided by Google Cloud that uses machine learning to extract meaning and metadata from unstructured text data. It supports features such as sentiment analysis, entity analysis, content classification, and syntax analysis. It also allows users to train their own custom models with auto-ML (Tyagi & Bhushan, 2023). Many studies have used Cloud Natural Language in city planning, such as analyzing the public comments on the proposed rezoning of the Gowanus neighborhood in Brooklyn, New York (Ray & Mathew, 2020). analyzing the tweets related to urban mobility in São Paulo, Brazil, to measure the public perception and satisfaction with different modes of transportation (Jin & Zhuo, 2023). Exploring online reviews of urban parks in London, UK, to evaluate the quality and attractiveness of the parks, as well as the user preferences and expectations (Pais et al., 2022).

2.4.2 IBM Watson Natural Language

This is an API provided by IBM that uses Deep Learning (DL) to extract meaning and metadata from unstructured text data. It supports features such as entities, categories, classifications, concepts, sentiment, emotion, relations, and syntax Fields (Vergara et al., 2017). This approach has been used to extract entities, relations, and concepts from urban planning documents and regulations (Vergara et al., 2017). In another research, scientists employed it to categorize the subjects and purposes of citizen inquiries in 311 service calls. They subsequently conducted content classification and constructed custom models to group the inquiries into various categories, including housing, sanitation, and safety (Shivam Solanki, 2022).

2.4.3 Graph databases and triple stores

These databases store data as nodes and edges, representing entities and relationships. They can store processed data from NLP engines and query them using graph languages such as SPARQL or Cypher (Yavar, 2017). Some examples of graph databases are Neo4j and Apache Titan. In the field of city planning and urban mobility, a graph database (OrientDB) and a triple store (AllegroGraph) were used to compare performance and functionality for storing and querying the semantic annotations of geospatial data (DeBellis, M. 2022). Another study could define the characteristics and patterns of urban mobility for the city of Mexico using a graph database (Neo4j) and a triple store (RDF4J) to compare their performance and scalability (Melikov et al., 2021).

2.4.4 TimeML

This is a markup language for temporal expressions in natural language texts (Luusua et al., 2023). It can be used to extract meaning from sentences that contain time information, such as dates, durations, intervals, and events. It also provides a standard way to normalize and represent time expressions in a machine-readable format. TimeML has been used in the context of city planning and urban mobility in several studies: to annotate temporal expressions in urban planning documents and regulations, the researchers used TimeML to create a corpus of urban planning texts with temporal information, which can be used for training and evaluating temporal information extraction systems (Trindade et al., 2017). In another study, researchers used TimeML to create a corpus of traffic accident texts with temporal information, which can be used to train and evaluate temporal reasoning systems and annotate temporal expressions in traffic accident reports (Lee et al., 2020).

Table 1. Comparison of Semantic Annotation Methods, Applicability, and Drawbacks. It is important to emphasize that the applicability and limitations mentioned in the table are context-specific to this research scope; the effectiveness of these methods can vary depending on particular use cases and implementations.

While this section presented alternatives to NLP, the post-data processing comparison in section 6.3 is also important for thoroughly evaluating their effectiveness in achieving the research goals. This assessment is meant to optimize resource allocation, considering factors such as cost and time while discerning the strengths and weaknesses of each approach. The ensuing comparison is designed to enhance research rigor, fostering methodological transparency and contributing to the broader generalizability of findings.

2.5 NLP AND URBAN DATA ANALYSIS

NLP has a promising potential as a technique for using underutilized urban data sources (Huai & Van de Voorde, 2022). However, NLP applications in city planning are yet in the initial stages. The most comprehensive and recent review of urban studies empowered by NLP was conducted by Cai (2021). The findings suggest that NLP applications fall within the scopes of urban design, mobility, land use, public healthcare system, management, and urban governance. Up to date, the main explored implications in urban studies are the following:

a) Establishing a better way of communication between city officials and local residents, facilitating citizen engagement, and enabling bottom-up approaches. The utilization of social media data through NLP techniques facilitates the detection of community interests and issues with respect to their geographic locations (Abalı et al., 2018), obtaining feedback and impressions (Estévez-Ortiz et al., 2016), feedback analyses (Sangil & Maceda, 2023), events detection (Hodorog et al., 2022). The Electronic Democracy European Network EDEN project illustrated a good NLP-based approach to enable a two-way dialogue between the public and the government by implementing testing pilots in different European cities (European Commission, 2019).

b) Urban hazards and disaster management during which NLP can be applied together with the social media Field (Neely & Collins, 2018) as a gateway for the diffusion of information and as an instinctive instrument for damage assessment, victim aid, urgent communication, and crisis monitoring. It has been vastly used during the COVID-19 (Zeidan et al., 2022) and rail transit emergencies in big cities (Fan et al., 2022). It proved effective in identifying and locating people's requests and prioritizing and affiliating interventions and duties during natural catastrophes (Nasution et al., 2022). It also helps in the quick generation of damage estimation reports (Pi et al., 2022).

c) Designation of Urban functions and territory analysis with NLP before the development of urban plans. The examination and definition of changes in urban structure and land use are normally accomplished by traditional methods such as surveying, manual remote sensing, and field research (Pissourios, 2019). Nowadays, the urban IoT systems adopted with NLP can gather data, automate semantic analysis, and identify scenarios. Deep learning (DL) can enable trained models of NLP to reflect human concepts (Muam et al., 2022).
d) Analyzing the functioning of the urban facilities and amenities, NLP is a reliable tool for assessing the lifestyle satisfaction degree of the built environment users based on the sentiment classification (Chang et al., 2022), outlines the individuals' perception regarding their living environments (Hu et al., 2019) and the functional categorization using crowd-sourced geographical data (Cao et al., 2021). Hence, NLP is also a resourceful instrument for determining housing prices and real estate values through semantic and sentimental analysis and real estate advertisements as a source of data (Blanchi et al., 2022).
e) In the context of urban mobility applications, numerous initiatives have been developed to leverage the low-cost and real-time data processing capabilities of non-textual data with high accuracy (Murçós, 2021). Analysis of public opinions on micro-mobility can offer good insights into current trends (Avetisyan et al., 2022) and challenges facing urban sustainability (Nicolas et al., 2021).

The possible contributions of NLP to urban planning research are plentiful and varied, contingent upon the unique objectives and requirements of each investigative undertaking. With the current state of the art, the following table can synthesize the subsequent approaches:

Table 2. NLP's Multifaceted Contributions to Urban Planning: Synthesized Approaches

NLP Application	Usage	Results
Text Mining and Analysis	- Application of NLP techniques to analyze large textual datasets (e.g., planning documents, news articles, social media posts, surveys)	Extract insights and prevailing trends relevant to urban planning.

Sentiment Analysis	Examination of sentiments in textual data	Understand public opinions and attitudes toward urban planning initiatives, aiding in strategy identification.
Geographical Information System (GIS) Integration	Extract geographical data from text, integrate into GIS software	Visualize and analyze spatial patterns and relationships between geographic features and urban planning, leading to more effective strategies.
Predictive Modeling	Construct predictive models for anticipating planning outcomes	Provide insights for decision-making by predicting results of different planning schemes or interventions.
Automated Summarization	Condense extensive textual data (e.g., planning documents) into concise summaries	Enhance urban planners' efficiency by saving time and improving understanding of voluminous text collections.

2.6 IMPACT OF COVID ON MAAS

The COVID-19 pandemic has wielded a significant impact on global urban mobility, manifesting in a decline in daily commutes to workplaces and educational institutions (Linares & G., 2021). These shifts have brought about substantial transformations in both individual lifestyles and patterns of mobility (de Palma et al., 2022). Notably, the landscape of urban mobility underwent a transformation marked by a surge in private car usage, a decrease in shared rides, an expansion of remote work practices, and a pronounced reduction in air travel and business-related trips (Schmidt et al., 2021). Recognizing the extent of the pandemic-induced disruption in urban mobility assumes paramount importance, as it serves as a cornerstone for devising data-driven solutions capable of effectively responding to the ever-evolving dynamics inherent in post-pandemic MaaS systems.

Decision-makers and mobility planners need to quantify and assess the pandemic's impact on urban mobility. This has spurred an immense amount of research. In order to comprehensively gauge the ramifications of COVID-19 on urban mobility, researchers and scientists have adopted a diverse range of methodologies (Abduljabbar et al., 2022). These approaches encompass the meticulous analysis of transportation data, the execution of surveys and interviews with the public, and the application of computer simulations and modeling techniques to anticipate the potential influence of mobility alterations on virus transmission (C. Zhao et al., 2022). As the investigation into pandemic-driven mobility shifts continues to unfold, advanced tools such as Sysrev, a machine learning-based systematic review platform, offer unique attributes that position them as robust contenders for the management of literature reviews. One notable feature of Sysrev is its ability to streamline the screening process, thus enhancing efficiency and facilitating collaborative screening and decision-making among multiple researchers and augmenting the review's overall reliability.

Initially, relevant search terms were formulated, such as (COVID's impact on urban mobility), to capture articles from the following databases: ScienceDirect, Tandf, Libsearch, and Primo. Leveraging Sysrev's integration with these databases, an extensive collection of articles was amassed, exceeding 13000 articles. The screening process was streamlined as Sysrev's algorithms prioritized articles based on relevance, see Fig. 8, and allowed for efficient data extraction and annotation. Insights gleaned from the selected articles were synthesized and analyzed to uncover patterns and trends surrounding COVID-19's influence on urban mobility.

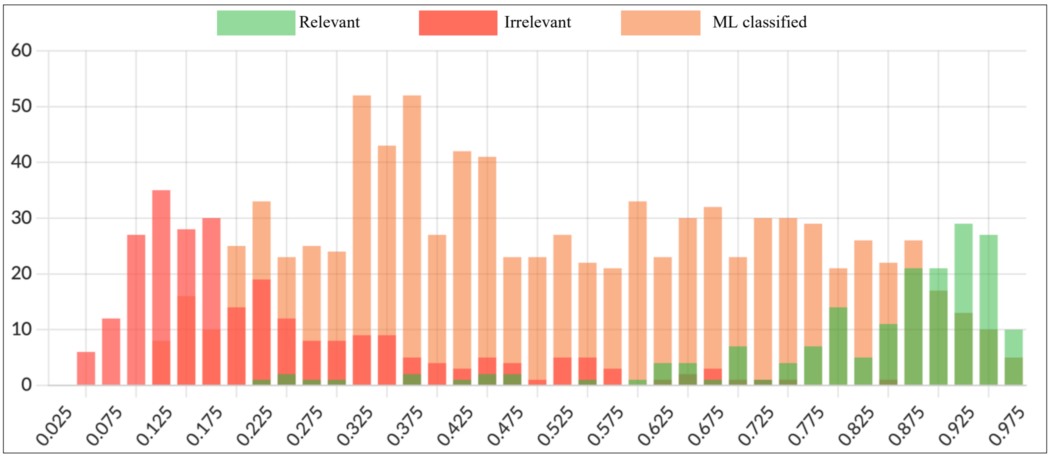

Fig. 8. Predictions Model for Inclusion for 1300 Studies on Mobility and COVID with sysrev. Source: The Author.

Based on the study results, the actions and policies implemented in response to public health emergencies were mainly reactive (Pascale et al., 2022). The authors focused on the resilience of urban systems to respond proactively to such emergencies. The findings indicate a lack of strategic planning for fair and equitable urban mobility, as recommended by Sustainable Urban Mobility Plans SUMP and Sustainable Development Goals (SDGs). The majority of publications in the period of 2020-2022 have focused on case studies evaluating the pandemic's impact on urban transportation.

While the environmental aspect of sustainability has received significant attention, limited research on the social aspect has been conducted. However, certain aspects of the pandemic's impact on society, such as technological developments in mobility services, have received considerable attention (Laliotis & Minos, 2022). This includes shared and micro-mobility, IoT solutions, and intelligent traffic systems to improve the urban mobility management (Tsvetkova et al., 2022). Many studies highlighted the need for more legislative and research efforts to ensure the implementation of smart and sustainable transportation solutions in cities.

The literature review revealed that most research has properly covered the spread of COVID-19 with the mobility of people (Shibamoto et al., 2022) through several methods, like structural modeling (Rafiq et al., 2022), time series analysis (Zargari et al., 2022) and activity travel model (Nguyen et al., 2022).

Nonetheless, the absence of a study examining the effects of urban mobility advancement gives rise to potential challenges. Firstly, crafting an informed decision-making system to assist individuals during the pandemic will be complicated in the absence of empirical studies. Secondly, evaluating the effectiveness of mobility development strategies and identifying avenues for improvement becomes difficult due to inadequate data availability. Lastly, comprehending the pandemic's spread with people's mobility choices proves difficult without a targeted analysis.

2.7 IDENTIFIED GAPS

Based on the literature review and the objectives set for this study, some of the identified research gaps are the following:

a) **Limited integration of data sources**: One of the gaps is the limited integration of data from various MaaS providers and other urban mobility sources. Many studies focus on specific MaaS platforms or individual data streams rather than considering a comprehensive and integrated data approach. This gap hinders the ability to analyze the full spectrum of mobility patterns and user preferences.

b) **Big data utilization challenges:** While real-time data is available from MaaS platforms, its effective utilization for dynamic route optimization and city planning remains an area of exploration. Incorporating big data for actionable decision-making poses technical, privacy, and scalability challenges that require further investigation.

c) **Evaluating the MaaS ecosystem:** the literature lacks standardized measurement metrics and evaluation frameworks for the MaaS ecosystem. To ensure a comprehensive understanding of MaaS data, it is crucial to establish a comprehensive analysis. This will allow for a holistic assessment of MaaS data and contribute to a well-rounded approach in the evaluation process.

d) **The pandemic impact**: the literature has primarily focused on the concept itself and mostly on the impact of the COVID-19 pandemic on MaaS operations. However, the role MaaS played in mitigating COVID has been overlooked. This study will address this gap by investigating how advanced and multimodal mobility systems have altered the spread of the pandemic.

e) **The evaluation of the distinctive features of MaaS organizations:** the existing literature lacks a comprehensive global analysis of MaaS organizations. Analyzing the integration levels of MaaS companies holds paramount importance. Such analysis provides a lens through which researchers can unravel intricate insights into the interplay between MaaS entities and the urban system.

By addressing these gaps, a meaningful perspective can be revealed for MaaS data for city planning purposes with seamless integration of MaaS systems within the urban system. The acquired knowledge is meant to contribute to more sustainable, efficient, and people-centric urban mobility solutions, leading to enhanced quality of life and greater resilience in the face of future urban challenges.

2.8 SUMMARY AND IMPLICATIONS

This chapter explored the expanding academic literature focused on contemporary urban mobility data and the emergence of novel mobility trends, with a spotlight on MaaS and its data-driven role in urban planning. The chapter attempts to explore MaaS benefits over conventional mobility systems in city planning and delves into existing MaaS literature to pinpoint research gaps, utilizing an SR approach. This investigation forms the foundation for the forthcoming chapters' exploration of the intricate MaaS data. The insights garnered from this review will serve as a launching point for further examination and analysis, facilitating the understanding of the dynamic interplay of the MaaS data for further examination in section 4.3 on the **MaaS Ecosystem**.

The review of technological advancements and market growth of MaaS serves a dual purpose. It establishes a comprehensive framework for defining the MaaS market more precisely while also facilitating the selection of appropriate data sources for a comprehensive exploration of the MaaS ecosystem. Further elaboration on this line of inquiry is presented in section 3.3, with a detailed examination of the specific data sources utilized, together with a discussion of the anticipated outcomes and insights.

Urban data processing tools, particularly NLP, are assessed for their potential to decipher text data for city planning, as evidenced in the existing literature. Building upon this foundation, section 3.4 will delve deeper into the practical implementation of NLP within the specific context of this research. Section 4.6 will expound upon the operational mechanics of NLP and elucidate its implementation, including key parameters, enhance comprehension of its pivotal role in data processing, and achieve the research objectives.

The obscure ramifications of the pandemic on urban mobility will also be analyzed, aiming to provide a holistic understanding of the COVID-19-MaaS intersection while addressing the specified research gaps.

As the literature review attempted to explain the multifaceted landscape of MaaS and the potential of its data, it becomes clear that a methodologically robust approach is essential to unlock more insights. Building upon the literature, the subsequent chapter will delineate the research design and methods employed in this study. By explicating the deliberate choices made in approaching data collection, analysis, and interpretation, the forthcoming chapter will provide a structured framework that bridges theoretical exploration with empirical investigation, ultimately propelling the quest to harness the power of MaaS data for effective urban planning solutions.

Overall, the chapter's exploration not only reveals evolving mobility paradigms but also emphasizes the need for meticulous investigation and innovative solutions to shape urban planning effectively.

The chapter provides an avenue to enhance the clarity of the research objectives, questions, and hypotheses. In essence, the refined framework can be summarized as follows:

- Research Objectives

Objective 1: Enhance data integration.

Develop methods to combine data from various MaaS providers and sources for comprehensive analysis in city planning.

Objective 2: Optimize big data usage.

Explore techniques to effectively utilize the substantial data from MaaS platforms to contribute to urban development.

Objective 3: Assess the pandemic's impact.

Analyze the effects of the COVID-19 pandemic on urban mobility patterns and examine how MaaS services have responded to and influenced these changes.

Objective 4: Examine MaaS organizational dynamics.

Evaluate the operational dynamics and integration approaches of MaaS organizations to understand their role and effectiveness in shaping urban mobility landscapes.

- Research questions

Question 1: How can examining MaaS data enhance our understanding of its unique characteristics and significance in shaping urban mobility patterns?

Question 2: Can the application of advanced AI tools such as NLP effectively extract insights from MaaS data to inform urban planning strategies based on the existing data?

Question 3: What are the implications of external disruptions, particularly the COVID-19 pandemic, on urban mobility patterns within the MaaS system?

- The hypotheses

Hypothesis 1: Integration and Characteristics of MaaS Organizations

MaaS organizations are more likely to possess characteristics such as public ownership, longer operational history, and a diverse range of mobility modes.

Hypothesis 2: Utilization of MaaS data for urban planning and sustainability

MaaS data can offer actionable insights for promoting urban sustainability and achieving SDGs through informed decision-making in urban planning processes.

Hypothesis 3: Role of MaaS in urban resilience and adaptation

MaaS plays a significant role in fostering urban resilience, particularly during external disruptions like the global pandemic.

Chapter 3: Research Design and Scoping

As urban environments become increasingly complex and interconnected, the need to harness the potential of MaaS data emerges as a critical endeavor in shaping the future of sustainable and efficient cityscapes. This chapter guides through the considerations that underpin the methodology chosen for this thesis, shedding light on the deliberate steps taken to unravel the potential that MaaS data holds within the domain of urban planning, with a focus on explaining the research design's details and the deliberate scoping of the study.

Section 3.1 translates the summary of the results acquired from the previous chapter and aligns it with the research questions and objectives. Afterward, the research scope and the potential contributions are narrowed down and defined accordingly. Section 3.2 discusses the process to be followed in the next two chapters, the employed approaches, and the research design. Section 3.3 is dedicated to presenting the data used in the study. Section 3.4 lists the kits and instruments used in the study and upholds their use. Section 3.5 deliberates how the research will proceed and the timeline of its execution. Section 3.6 provides the analytical approaches for each part of the research in hand. Finally, section 3.7 scrutinizes the ethical concerns of the research and its challenges.

3.1 CONCEPTUAL FRAMEWORK

The research at hand seeks to comprehensively define and examine the MaaS ecosystem and the diverse forms of MaaS data it delivers, with the aim of exploring its potential applications in the realm of city planning and highlighting any overlooked prospects. To achieve this goal, it is crucial to acknowledge and overcome the challenges related to this research topic.

This thesis starts by expounding on the various components of the MaaS ecosystem, providing a detailed breakdown thereof, followed by a discussion about MaaS-related data, which helps to examine various sources and types of data in the MaaS system and facilitate its understanding.

Then, the research explicates the instruments and tools employed in the study in relation to the research objectives and the data used. By doing so, the methodology adopted to achieve the research objectives will be clarified.

The proposed study design is articulated based on a hybrid methodology of qualitative and quantitative research methods. Specifically, the study starts with an extensive literature review and then leverages a range of data collection methods, including various industry data processing and rigorous data analysis techniques, to achieve the research objectives effectively.

The literature review component of the study, presented in the previous chapter, involves an in-depth analysis of pertinent academic and scientific publications to place the research question within the current knowledge landscape. This component of the study enables the identification of existing gaps in the literature and provides insights into potential areas of further investigation.

The qualitative research component of the study involves conducting comprehensive evaluations of the study cases in the industry to build the main database, examine it, and gather relevant insights about the topic under investigation. These assessments´ results are integrated within the data sets to elicit rich and detailed information about the research question, which will be crucial in understanding the complexity and nuances of the topic.

In addition, the quantitative research component of the study will involve the analysis of large datasets to provide a broad and statistically significant perspective on the topic. This component of the study enables the identification of trends and patterns in the data, which facilitates the formulation of well-informed conclusions and recommendations.

At the end of the presented chapters of this research, an **excursive chapter** is dedicated to investigating how the pandemic has impacted the way people move in cities. To conduct a robust study on MaaS, it was crucial to have a deep understanding of how the pandemic has reshaped urban mobility. This part of the research seeks to investigate the pandemic's influence on mobility services, which has become an increasingly important subject. While prior studies have identified factors to consider when studying the pandemic's impact on mobility services, there is still a research gap when it comes to understanding how changes in the transportation system relate to the spread of the pandemic.

To bridge this gap of knowledge, this research conducts a comprehensive analysis to assess the impact of the pandemic on mobility services by drawing upon the context of Germany as a case study. Through this analysis, the research will seek to answer several key questions. For instance, how has the demand for mobility services changed since the start of the pandemic? Have there been changes in the usage patterns of various mobility modes? How have the different mobility modes been affected by the pandemic? Essentially, what was the impact of the pandemic on the MaaS system, and has it had any retrospective effects?

3.2 METHODS

The primary objective of the study is to assess the outcomes of MaaS systems and classify them based on their practical applications in urban planning practices. The research methodology encompasses a comprehensive four-stage process, comprising the definition of the MaaS concept and its corresponding data, the development of a structured methodology for MaaS data collection and extraction, the organization and classification of the collected data according to urban planning practices, and the evaluation of the compatibility level between the extracted MaaS data and urban planning practices. The process is elaborated in detail in Chapter 4: to provide insights into the utilization of MaaS data within the framework of urban planning.

To achieve the research objectives, the approach involves gathering MaaS data, including its diverse types, quantity, and quality. The data is then methodically organized and classified into well-defined domains to assess its applicability to city planning practices. The collected keywords extracted from the exported MaaS data will be tokenized, classified, and placed with the matching domain of city planning.

In this study, the investigation is conducted into the applicability of MaaS data in city planning, utilizing a comprehensive set of procedures. Firstly, specific aspects of city planning that can be analyzed using MaaS data will be identified. This will encompass the examination of smart city practices and recommendations relating to the SDGs, which will be presented in the following chapter, section 4.5.

Secondly, pertinent MaaS data will be collected and organized, encompassing transportation service types, operations, MaaS purposes, offers, and associated information. Thirdly, the MaaS data will be subjected to cleaning and pre-processing procedures to ensure its suitability for analysis. This will include the removal of any erroneous or incomplete data, formatting it into a suitable structure, and selecting the most relevant data for the specific city planning queries being pursued, see Fig. 9.

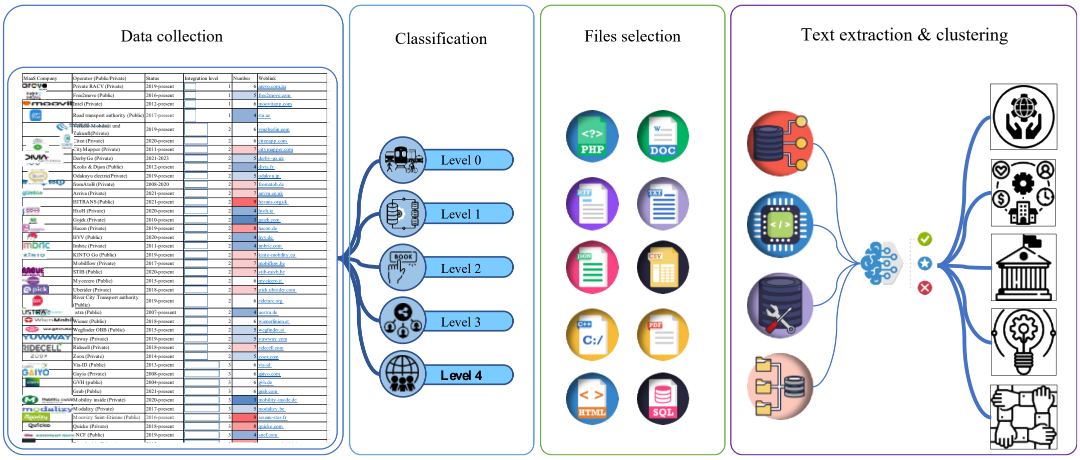

Fig. 9. Process of MaaS Data Collection, Processing, and Classification. Source: The Author.

Next, the analysis results will be interpreted, and the applicability of the MaaS data concerning the city planning subjects under investigation will be assessed. This will involve identifying any patterns or trends in the data and discussing their implications for city planning decisions, which will evolve in the definition of the suitable use cases in Chapter 5:.

Furthermore, the findings will be compared and discussed with analogous research works, such as pertinent city planning, policymaking, and transportation management studies in Chapter 6:. The conclusion will be presented in Chapter 7: in a clear and concise manner, highlighting significant insights and providing recommendations for future city planning.

The **excursive chapter** employs a different approach to explore the hypothetical effects of mobility development on individuals' mobility during periods of crisis. To this end, this chapter undertakes a correlation analysis to investigate the relationships between a range of factors. Specifically, the Spearman correlation analysis is utilized to explore the interplay between three variables. This parametric test enables the evaluation of the strength and direction of the relationship between the variables, even when the data is not normally distributed or in the presence of outliers.

The objective is to construct a correlation matrix, which will be employed to scrutinize mobility trends in five distinct categories. There, that chapter is crafted to offer a thorough comprehension of the relationship between mobility advancement and people's mobility during crises. Furthermore, it will help evaluate how the progress of urban mobility systems influences urban mobility during times of crisis.

3.3 DATA ACQUISITION

The acquisition and processing of large-scale multisource data remains a significant challenge for academic research projects, which can constrain and limit the types of research that can be conducted in the field (Ye et al., 2021). Despite the availability of enormous volumes of continuously generated and open-source data, they are usually limited to certain research scopes and periods (Wiltshire & Alvanides, 2022). To conduct an appropriate empirical study of urban mobility, multi-sourcing within the identical surveillance and observation period can be the quintessential solution, yet it is a highly demanding and complicated procedure.

After defining the MaaS ecosystem and data, explaining the MaaS system integration levels will be necessary to classify the MaaS systems of the companies included in this study.

The selection of the data sources out of MaaS companies is based on several informational references, including:

- Industry reports: Review various reports on the global MaaS market and identify companies that are considered major players in the market.
- News articles: Search for news articles on MaaS companies and identify companies that have been making significant strides in the industry.
- Online research: Conduct online research on MaaS companies and analyze their websites, social media presence, and customer reviews to evaluate the quality of their services.
- Expert opinion: Consult with experts in the field of mobility and MaaS to gather insights on the most innovative and successful companies in the industry.

Marketing materials, such as flashy advertisements and promotional brochures, were excluded from the data selection process as they often prioritize sales pitches over providing objective information about MaaS organizations. Additionally, sources lacking credibility, like obscure blogs or unverified social media accounts, were omitted to ensure the reliability of the data collected. These sources may not have the expertise or authority within the MaaS domain to provide accurate and relevant information. By excluding such sources, the integrity of the dataset was maintained, and the focus was directed toward reputable sources that offer substantive insights into the MaaS ecosystem.

3.4 DATA PROCESSING INSTRUMENTS

Given the vast amounts of structured and unstructured data characterized by heavy textual content, it is imperative to establish an efficient mechanism for analysis. Consequently, analysis techniques have become increasingly necessary. The data of the study involves vast and complex data sets that traditional data processing tools cannot handle. These techniques face a range of challenges, such as data privacy and confidentiality, storage, analysis, sharing, and transfer, as well as visualization, retrieval, and querying. These data sets share three common features, namely volume, variety, and velocity. To address these challenges, big data analysis techniques, including Machine Learning (ML), Data Mining (DM), DL, and NLP, are typically used.

- **Machine learning** is a technique for training machines to understand and learn from data without being explicitly programmed. It is also a subset of AI, which is often described as the ability of a computer or a machine to imitate and simulate human behavior.
- **Data mining** is the process of looking for patterns in massive amounts of data using techniques that combine machine learning, statistics, and database management systems. This approach is used in this procedure to detect relevant data features.
- **Deep learning** is a specialized field within machine learning that employs deep neural networks to acquire knowledge from data. A deep neural network, which is characterized by its multi-layered structure, is utilized in DL. Prior to the development of DL-based NLP models, computer-assisted analysis of this function was not possible and could not be evaluated systematically. With the use of NLP, analysts can filter through enormous amounts of unstructured text data to uncover relevant information.

1. **Natural Language Processing**

NLP is a category of AI. It is the ability of a computer program or software to comprehend the human simple and natural language, as it is verbal and transcribed or written form. In other words, it enables computers to understand languages in a comparable way to humans. NLP has been developed and used for more than 50 years and has a linguistics background. It has a multiplicity of real-world applications in various fields, including medical research, search engines, and business intelligence. There are two main stages to NLP: data pre-processing and algorithm elaboration and development. Data pre-processing involves preparing, organizing, and cleaning text data for machines to analyze. By highlighting the text features, it enables the algorithm to process the data in several ways:

- **Tokenization** by partitioning the text into smaller chunks or units to be operational.
- **Stop word removal** by eliminating conjoint words and expressions from the text so unique words and the most informative ones remain.
- **Lemmatization and stemming** by keeping the root form of words for processing.
- **Part-of-speech tagging is done by marking texts´ meanings established in** the context, such as nouns, verbs (conjugations), and adjectives.

An algorithm is created to process the data once it has been pre-processed. While there are several types of NLP algorithms, the most common and widely used categories are the rules-based and ML-based systems (Casey et al., 2021):

- **Rules-based system:** a system that employs rules developed by humans to categorize, retain, and process data. In constructing this system, careful attention must be given to the language rules. This approach was utilized in the pilot stages of NLP development and continues to be utilized ever since.

- **Machine Learning-based system:** the efficacy of NLP is significantly influenced by ML-based systems, where statistical techniques are utilized in ML algorithms. These techniques enable NLP algorithms to learn and refine their processing and performance. Through the analysis of vast amounts of data, these algorithms progressively enhance their techniques and acquire the ability to execute tasks based on the training data they receive. In the context of NLP, the algorithms utilize a combination of ML, DL, and neural networks to refine their language rules and improve their processing capabilities over time.

3.5 PROCEDURE AND TIMELINE

In this research, the data collection and study procedure have evolved to adapt to changing circumstances and research objectives. Here is an outline of the procedure:

1. **Initial Focus on Hamburg, Pre-Pandemic (Mid-2019 – 2020):**

- The research began in mid-2019 with a primary focus on studying the MaaS use case of Hamburg, Germany.
- Data collection efforts commenced with a specific focus on Hamburg's MaaS system.

2. **Pandemic Considerations (2020 - 2021):**

- Before processing the collected data from Hamburg, the COVID-19 pandemic emerged, changing the urban mobility dynamic and prompting a shift in research priorities.
- Parallel research has begun to address the impact of the pandemic on urban mobility, reflecting the ongoing event and updating the research knowledge. Accordingly, a dedicated chapter was added (the excursive chapter).

3. **Global Vision (2021 - 2022):**

- With the post-pandemic, and after extensive research and discussions with experts, as well as presenting the research at the Intelligent Transportation Systems ITS World Congress 2021, a reassessment of Hamburg's MaaS system led to the decision to expand the scope.
- The research transitioned to a global perspective, aiming to encompass prominent MaaS organizations worldwide, with joining MaaS Alliance that incorporates more than 100 members and working groups on MaaS, from public authorities, transport/mobility service providers, technology solutions providers, associations, consultancy, research, and innovation.
- This shift in focus required a broader data collection effort.
- A research paper investigating the impact of MaaS and advanced mobility systems on the pandemic was published and presented at the International Conference on Sustainable Mobility and Safety (IC-SMS). Is

4. **Adoption of NLP (2022 – Mid-2022):**

- To process the extensive data from global MaaS organizations more accurately and efficiently, NLP techniques were considered and adopted.
- A dedicated phase for training and research was introduced to familiarize oneself with the feasibility and applicability of the relevant AI and NLP tools and techniques. This step aimed to ensure proficiency in employing AI and NLP effectively in the later stages of the research.

5. **Phased Data Collection (Mid-2022-2023):**

- The initial research included a sample of 50 MaaS companies. Based on it, a research paper entitled: "Exploitation of MaaS Data for City Planning" was published in the Xplore digital library of the IEEE (Institute of Electrical and Electronics Engineers) and presented at the 7th International Conference on Intelligent Transportation Engineering (ICITE).
- The research findings were also presented at various international conferences and events, such as Smart Cities Sofa events, MaaS Alliance, and business conferences.
- Feedback from these presentations and continuous improvement efforts informed the next steps.

6. **Expansion and Enhancement (2023 - Mid-2023):**

- Building upon the feedback received and the advancements in research methodology, an updated version of the research was prepared at the beginning of 2023.
- The data sample was expanded to include information from 200 MaaS companies, providing a more comprehensive dataset.
- Advanced NLP techniques were implemented to further enhance data analysis capabilities. Additionally, state-of-the-art NLP libraries and tools, like spaCy and NLTK, were utilized to enhance data analysis capabilities.
- The research was refined to match domains in city planning with specific use cases derived from MaaS data.

7. **Research Conclusion (Mid-2023)**

- The research has culminated in a comprehensive study in the field of MaaS and city planning.
- Its findings have the potential for a good contribution to urban planning and smart transportation, paving the way for more efficient, sustainable, and livable cities.

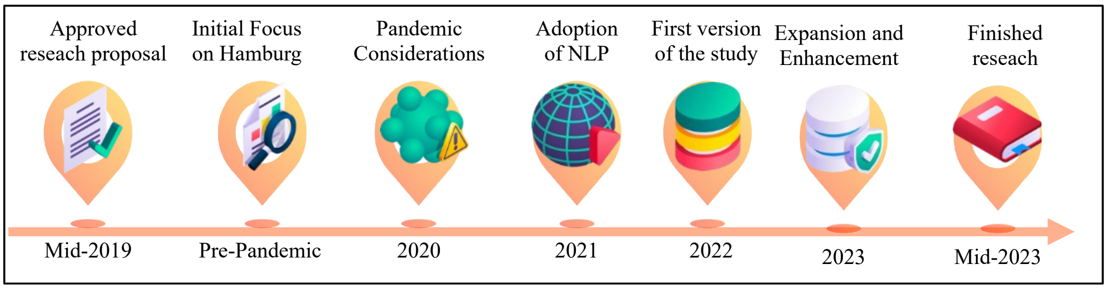

Fig. 10. Research Progress Timeline. Source The Author

This evolving research procedure highlights the adaptability and responsiveness of the study to changing circumstances, emerging technologies, and the need for a more comprehensive understanding of the global MaaS landscape.

3.6 THE ANALYTICAL APPROACH

3.6.1 Comparative Analysis of MaaS Integration Levels: Private vs. Public

The t-test is utilized to determine if there is a significant difference between the means of two groups, in this case, the integration levels of private and public MaaS companies, to assess whether there is a statistically significant difference in their integration level based on the provided sample of 200 organizations, here is the followed approach:

1. **Hypotheses Formulation:**

- Null Hypothesis (H_0): There is no significant difference in the mean integration levels between private and public MaaS companies. In other words, the means are assumed to be equal (μ private = μ public).
- Alternative Hypothesis (H_1): A significant difference exists in the mean integration levels between private and public MaaS companies. The means are assumed to be unequal (μ private ≠ μ public).

2. **Data Collection:**

- Data on the integration levels of 200 organizations are collected, as seen in section 4.2, with 170 belonging to private companies and 30 to public companies.

3. **T-statistic Calculation:**

- The t-test is used to compute a t-statistic with SPSS based on the means and standard deviations of the two groups and their respective sample sizes.

4. **Determination of Degrees of Freedom:**

- The degrees of freedom depend on whether equal variances are assumed or not. The degrees of freedom affect the distribution of the t-statistic.

5. **P-value Calculation:**

- The p-value quantifies the probability of observing a difference as extreme as the one observed, assuming the null hypothesis is true. A small p-value (typically less than 0.05) leads to the rejection of the null hypothesis in favor of the alternative hypothesis.

6. **Decision-Making:**

- If the p-value is lower than the chosen significance level (e.g., 0.05), the null hypothesis is rejected. This implies that there is a statistically significant difference in the mean integration levels between private and public MaaS companies.

7. **Results Interpretation:**

- If the null hypothesis is rejected, it indicates that there is evidence to suggest that one type of company (either private or public) is more likely to be integrated than the other, based on the sample data provided by 200 organizations.

3.6.2 Relationship between the integration level and the year of establishment

A chi-square test is a statistical test used to determine whether there is a significant association between two categorical variables in a dataset. In this case, a chi-square test is applied to assess whether the number of years since the creation of a MaaS company has a relationship with the integration level of these companies. Integration level and years since establishment are both categorical variables. The test is applied as follows:

1. **Null Hypothesis (H_0)**: The null hypothesis in this case is that there is no significant association or relationship between the number of years since the creation of a MaaS company and its integration level. In other words, the variables are independent.

2. **Alternative Hypothesis (H_1)**: The alternative hypothesis is that there is a significant association or relationship between the number of years since establishment and integration level.

3. **Chi-Square Test**: The chi-square test is conducted by comparing the observed frequencies of each combination of integration level and years since establishment in the sample to the expected frequencies that occur if the variables were independent. The test calculates a chi-square statistic, which represents the degree of deviation between the observed and expected frequencies.

4. **P-Value**: The chi-square test generates a p-value, which refers to the probability of obtaining the observed results if the variables were independent. If the p-value is small, less than 0.05, the null hypothesis is rejected, and the study can conclude that there is a significant relationship between the variables.

3.6.3 Relationship between the integration level vs the number of mobility modes

A chi-square test is used here as well, and it will help assess whether the observed frequencies of categories within these variables differ significantly from what can be expected by chance alone. It will assess the relationship between two categorical variables:

1. **Integration Level**: This variable has three categories - low, medium, and high.

2. **Number of Mobility Modes**: This variable represents the number of mobility modes provided by MaaS companies, with multiple categories ranging from 2 to 8. See Appendix D.

The chi-square test can help support the idea that there is a statistically significant relationship between these two variables based on the provided data from 200 organizations. Here is how the test works:

1. **Null Hypothesis (H_0)**: The null hypothesis in this case is that there is no relationship between integration level and the number of mobility modes provided by MaaS companies. In other words, the variables are independent.
2. **Alternative Hypothesis (H_1)**: The alternative hypothesis is that there is a relationship between integration level and the number of mobility modes provided by MaaS companies, which means that the variables are dependent.
3. **Chi-Square Test Statistic**: The chi-square test calculates a test statistic that measures the difference between the observed and expected frequencies of the categories in the contingency data.
4. **P-value**: The chi-square test also provides a p-value. This p-value reflects the probability of observing the experimental relationship between the variables if the null hypothesis were true. A small p-value, typically less than 0.05, indicates that the relationship is statistically significant.

3.6.4 MaaS data exploitation for city planning

The analysis part of the study involves exploring the collected MaaS data to identify patterns, trends, and relationships relevant to city planning domains. The analysis process involves various statistical and computational techniques to enable the extraction of meaningful insights from the data.

For instance, descriptive statistics are used to summarize and visualize the central tendency and variability of the MaaS data. Additionally, inferential statistics, such as correlation and regression analysis, are used to identify relationships between different variables in the MaaS data. Machine learning techniques like clustering, classification, and prediction algorithms are also utilized to analyze the MaaS data. These techniques help to identify hidden patterns and relationships that may not be easily identifiable through traditional statistical methods.

The analysis part of the study is essential for making sense of the MaaS data collected and drawing meaningful insights that inform city planning decisions.

3.6.5 Impact of the pandemic on MaaS

The effects of the pandemic on MaaS are being analyzed in the present research, in a separate chapter, with a view to determining whether there exists a statistical relationship between mobility trends and the Smart Mobility Index (SMI).

The strength of this relationship is measured by the correlation between a systematic increase or decrease in one variable and a corresponding rise or decline in the other variable. Pearson's R is the preferred metric for assessing correlation strength, with 0 indicating no relationship and 1 denoting the ideal outcome.

This study uses Mobility Trends (MT) as the response variable and SMI as the predictor. However, the third variable, Contacts between Individuals (CbI), is expected to have multiple connections between MT and SMI. Accordingly, the strength of these connections determines the prediction links MT and SMI. It is essential to ensure that the correlations tested in the study are accurately reflecting the data and provide a response to the research inquiry.

Given the number of variables involved, other measures of correlation strength, such as Cohen's D, a line graph, or a scatterplot, would not be appropriate. Therefore, the approach of using Pearson's R is deemed the most suitable for the study to assess the statistical relationship between MaaS and the pandemic's impact.

3.7 ETHICS

The inundation of fast, comprehensive, and indexed data raises several ethical inquiries about privacy, datafication, geo-surveillance, and data processing practices, such as social sorting and preventive authority. Given that the primary focus of this research is to derive value from data related to people's mobility, it must adhere to the fundamental human right of privacy, which entails the ability to determine who has access to confidential information and to make decisions regarding its disclosure (Elwood & Leszczynski, 2011). Additionally, this research's objective is to translate actionable data analytics into approaches with data-driven solutions, placing it within the restrictions of the ethical data standards (Kitchin, 2016) defined by the ethics guidelines for trustworthy AI fields (The European Commission, 2019).

Two standards are employed to ensure adherence to ethical practices in this research. The first is the confidentiality of subjects, which guarantees that only those who are actively involved in the conducted research have access to the information gathered (Nelson et al., 2022). Another fundamental principle is privacy, which can be upheld by anonymizing the data utilized so that researchers are unable to identify any individual subject throughout the entire duration of the study (Martinez-Balleste et al., 2013).

Chapter 4: Model Development and Data Processing

This chapter starts with the data collection process, the criterion, and the reason behind choosing the database elements in section 4.1. To further enhance the clarity of the discussion, section 4.2 provides a systematic breakdown of the MaaS system integration levels, which enables a reasoned classification of the MaaS systems considered in this study. This is followed by a comprehensive exposition of the MaaS ecosystem in section 4.3, elucidating the constituent elements and the types of data that can be extracted from it. In section 4.4, the distinction between structured and unstructured data is presented, highlighting their respective properties and analytical potential.

In the context of this research, NLP has been identified as an effective solution for processing vast amounts of text-heavy data. However, previous research has highlighted concerns regarding the opaque nature of NLP implementations and its usage as a Blackbox[4], which can undermine the credibility of the findings and obscure the underlying settings and parameters. To address these challenges, section 4.6 offers a detailed exposition of the model development process, the implementation, and the techniques used. The system architecture is also presented, accompanied by an analysis of different options and the logic behind the selected approach. In addition, the section elaborates on the data pre-processing, algorithm development, and processing pipeline, which were employed to derive the research outputs.

The structure of the sections in this chapter is illustrated in Fig. 11. First, the identification of ecosystem elements and clarification in section 4.3 help to identify MaaS-related data. From section 4.3, this data will be classified according to their relevance to city planning and SDGs domains, according to section 4.3, and the NLP system processing is explained in section 4.5.

[4] A "black box" is a system that can be comprehended solely in terms of its inputs and outputs, thereby rendering its internal workings opaque and difficult to interpret.

Derived from insights gathered in preceding chapters and established literature, the intricacies of the MaaS ecosystem are further illuminated. Moreover, the clarification of MaaS data originating from various sources is provided, along with the procedure for identifying relevant SDG domains for urban planning. This process lays the groundwork for subsequent stages driven by NLP techniques.

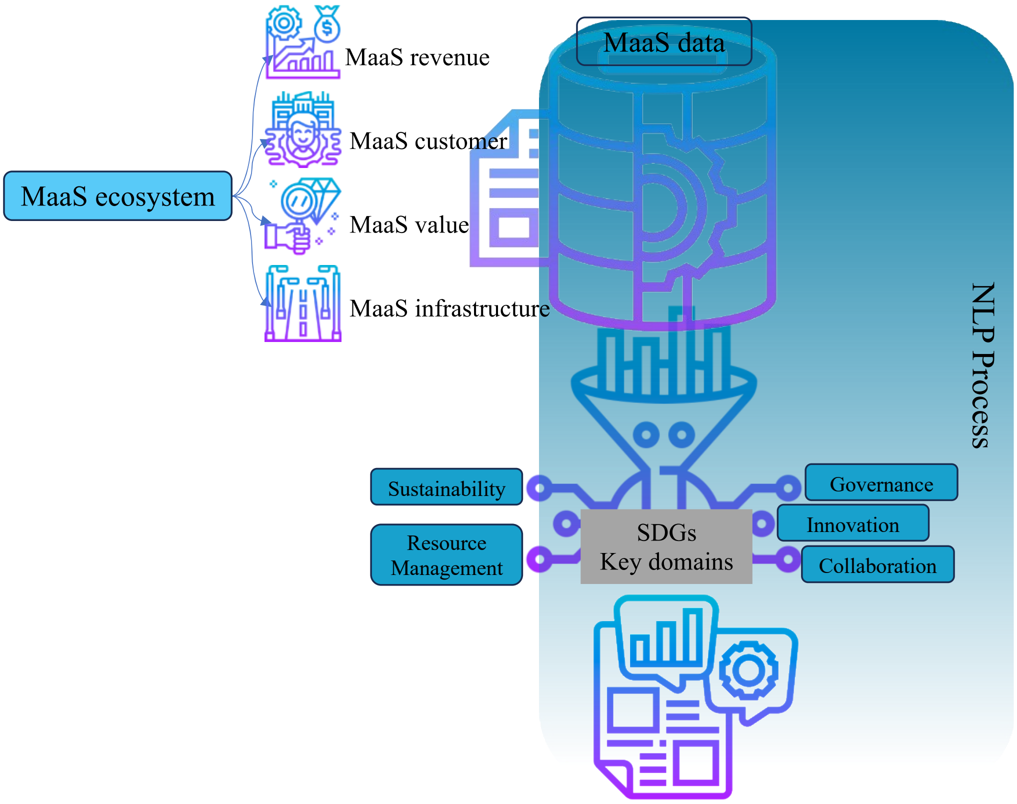

Fig. 11. The Process of Defining Data Types for MaaS and SDGs. Source: The Author

4.1 DATA COLLECTION

In this research, the significance of the data collection method, especially when dealing with MaaS companies, cannot be overstated. Therefore, this section outlines how the dataset of the MaaS organizations, in 1)a)Appendix D, have been assembled. This section explains the process of the organizations' selection and the parameters related to the dataset assembly. The objective is to shed light on the data collection approach, ensuring data accuracy and dependability, which, in turn, bolsters the quality of the research findings.

4.1.1 Criterion Establishment

The first stage of selecting appropriate MaaS organizations has been detailed in section 3.3. However, a second stage with the following points is also considered to validate the eligibility of an organization for extracting meaningful data:

- **Source Identification**: Multiple sources are explored to select the pertinent MaaS organizations. These sources encompass industry reports, directories, governmental records, and dedicated transportation service websites. However, to differentiate technical data from marketing and irrelevant data, the selection is based on the context, the source's credibility, and whether the data provides important information rather than promotional or unrelated content.
- **Web Scraping**: Web scraping techniques are employed to extract specific data points, such as company names, types, websites, establishment years, integration levels, and the count of mobility modes. The script utilized to retrieve this information from the official websites of these organizations is presented in 1)a)Appendix A.
- **Cross-Verification**: The validation of data from multiple sources is pivotal to ensure data accuracy and reliability. This entails cross-referencing data obtained from websites with information accessible in public records or industry databases.

4.1.2 Rationale for selected parameters

- **Company Name**: This parameter serves as a unique identifier for each organization, facilitating easy reference.
- **Type**: Categorizing organizations based on their type (public/private) within the MaaS ecosystem provides essential context. Public organizations, often associated with government or municipal entities, can have a direct impact on policymaking, regulation, and public transportation provision. They play a leading role in shaping the overall mobility landscape within a city. On the other hand, private organizations, including technology providers and aggregators, influence the technological infrastructure and user experience of MaaS platforms. Understanding the prevalence and roles of each, public and private, is essential for this research to have a balanced and operative dataset that provides diverse insights and gain a more comprehensive understanding of their impact on other factors.

- **Website**: The inclusion of website information not only aids in data verification but also provides a gateway for data collection.
- **Year of Creation**: This parameter allows for an understanding of the establishment timeline, which can be indicative of an organization's experience and maturity.
- **Level of Integration**: Evaluating the extent of integration of various transportation modes within the MaaS ecosystem can offer an overview of each organization's contributions. More details are provided in the following section, 4.2.
- **Number of Mobility Modes**: This parameter assesses the variety and diversity of mobility services provided by each organization. A diverse range of transportation options enhances accessibility, optimizes user experiences, and promotes efficient resource utilization. By integrating various modes such as public transit, ridesharing, biking, and walking, MaaS platforms offer users seamless journeys and contribute to environmental sustainability by promoting eco-friendly transportation options. The number of mobility modes reflects the platform's ability to cater to diverse user needs and preferences while supporting broader societal and environmental goals.

4.2 INTEGRATION LEVELS OF MAAS

The categorization of MaaS systems into tiers is a critical factor in determining their level of integration. Adopting a systematic approach to monitor the progress of MaaS development across diverse levels through the clustering of MaaS systems enables a better analysis of their data types and usability. Subsequently, a tailored strategy can be formulated, considering the unique features of each MaaS system.

Cluster analysis can afford a more detailed inspection of MaaS systems at each level of integration, see Fig. 12. The identification of commonalities and patterns among MaaS systems in each cluster provides a better perceptivity into their data types and usability. Armed with this information, a comprehensive strategy can be developed to align with the unique features of each MaaS system. According to Jana Sochor (2018), MaaS systems are commonly classified from Levels 0 to 4, as follows:

- **Level 0: No integration**; the service provider offers distinct mobility mode services at this level. Hitherto, there is no data interaction between different transportation modes.

- **Level 1: Integration of information or Data interaction**; at this level, the introduction of data connection and interaction starts between several means of transportation. After the user finishes one travel mode, the user can be directed to the next travel mode by the service provider. The trip data from the previous travel mode can be used by the following travel mode. The best example of this level is Google Maps.
- **Level 2: Integration of booking and payment with seamless data interaction.** The service at this level focuses on one-off journeys and might be a logical addition to a trip planner, including tickets for public transportation, taxis, or other forms of transportation when practical. The users do not need to interact with multiple service providers during their trip, and they can integrate all transportation services into one interface.
- **Level 3: Integration of the service offer**; the services of this level comprise deals and liabilities. The full alternative to automobile ownership, with a focus on the consumer's entire mobility requirements and the upgraded consumer appeal of the transport service providers to the users with no access to other separate services. Overall, these are the additional values of Level 3.
- **Level 4: Integration of societal goals**; this level embodies the fusion of societal objectives. As an illustration, the inclusion of economic transactions on Levels 2 and 3 (as opposed to Level 1) offers an extra opportunity to mediate financial incentives for selecting more environmentally friendly modes of transportation, adjusting travel periods to off-peak hours, etc.

Fig. 12. The Analyzed Corporations Mapped the 5 Integration Levels of MaaS.
Source: The Author.

However, while this classification was implemented during the initial research phase involving 50 MaaS companies, see Fig. 12. It was not carried forward into the second stage (involving 200 entries) due to the complexities it presented. To simplify this classification procedure and adapt to the dynamic nature of these organizations, this study opted for choosing three classes instead, see Appendix D:

1. **Basic Integration (Low):** This category encompasses the lowest levels of MaaS integration. At this stage, there is limited data interaction between transportation modes, mainly focusing on information exchange and navigation assistance.
2. **Intermediate Integration (Medium):** Intermediate integration includes seamless booking and payment across various transportation modes within a unified interface. Users can access and pay for different services through a single platform.
3. **Advanced Integration (High):** This category represents the highest levels of MaaS integration. It involves comprehensive solutions that cover the entirety of a user's mobility needs. Advanced integration extends to societal objectives and includes incentives for eco-friendly transportation choices.

In this study, the level of integration serves as a key indicator of the effectiveness and success of a MaaS system in providing seamless, sustainable, and user-centric transportation solutions within urban environments. As such, it becomes a crucial parameter for comparison when evaluating different MaaS offerings and their impact on urban mobility and sustainability.

For instance, cities experience significant advantages at an advanced level of MaaS implementation. Advanced MaaS integrates various transportation modes into a seamless network, ensuring efficient movement within the city and providing users with convenience, reduced travel times, and fewer disruptions. They consider societal objectives such as reducing traffic congestion, lowering emissions, and promoting sustainable transport, leading to enhanced environmental targets, improved air quality, and contributions to global climate change efforts. Utilizing data analytics for optimized routes and resource allocation enables cities to make informed decisions, allocate budgets efficiently, and respond dynamically to changing mobility patterns. Integrated MaaS streamlines administrative processes, payment systems, and infrastructure planning, resulting in cost savings, enhanced resource utilization, and increased investment attraction (Sarasini et al., 2017). Additionally, MaaS at advanced levels prioritizes user needs, promotes social inclusion, addresses mobility gaps, and reduces disparities, fostering a satisfied and loyal user base (Sakai, 2019). Collaboration between public authorities, private companies, and technology providers is crucial at this level, fostering innovation, leveraging private sector expertise, and creating a robust ecosystem.

4.3 MAAS ECOSYSTEM

In the realm of MaaS, attention is often captured by the most conspicuous aspects: the users, the infrastructure, and the service providers. These elements, much like the tip of an iceberg, are readily seen and commonly acknowledged. However, beneath the surface, a complex and intricate network of data-related components is maintained, akin to the submerged bulk of an iceberg that is often kept concealed from view. Fig. 13 illustrates the concealed elements, the unseen foundations of MaaS, which encompass vital aspects such as marketing, management, payments, customer relationships, communication, and data related to energy and fuel. While these elements may not always be immediately apparent, they play an indispensable role in the functionality and success of the MaaS ecosystem.

Fig. 13. The Unseen Foundations of MaaS. Source: The Author.

To enhance the understanding of MaaS models and their potential configurations, a conceptual framework has been developed by combining the MaaS Model Canvas with a morphological approach and consolidating the pertinent elements under the framework, as outlined in 1)a)Appendix E. The previously conducted systematic literature review is employed to augment the framework with additional details and information. This facilitated the development of 4 layers comprising the MaaS ecosystem components, see Fig. 14. The framework serves as a tool for comprehending MaaS features and the derivation of data, thereby supporting subsequent MaaS data clustering efforts. By highlighting the symbiotic relationship between various configurations, the framework provides a good starting point for the acquisition of MaaS data.

As demonstrated in the literature review, section 2.2, there has been a lack of research attention directed toward the MaaS business models (Reck et al., 2020).

However, MaaS business model alternatives are quite use-case specific, be it in terms of the types of mobility services (Chen & Qiu, 2019) or the locality (Jokinen et al., 2019) (P. Cooper et al., 2019). Hence, to ensure comprehensive coverage of various MaaS platforms and typologies, it is imperative to establish a framework for assessing MaaS systems. This framework will facilitate the identification and inclusion of relevant aspects, enabling their categorization and contributing to a holistic understanding of MaaS data.

MaaS ecosystem operates through four critical layers based on the Business Model Canvas (BMC), originally developed by (Osterwalder et al., 2005). The BMC is composed of nine structural components that depict the model and its operations (Osterwalder & Pigneur, 2010). Various methods of adapting the BMC to MaaS have been implemented (König et al., 2016) and followed the structure of the four layers (Lygnerud & Nilsson, 2021), (Polydoropoulou et al., 2020), as illustrated in Fig. 14.

Firstly, the Revenue Structures Layer, highlighted by Kramers et al. (2018), underscores financial sustainability through cost structures and diverse revenue streams. Secondly, the Customer Structures Layer, as emphasized by Vij et al. (2013), focuses on understanding and engaging consumers effectively, enhancing relationships and communication channels as outlined by Zhu et al. (2017) and Semanjski & Gautama (2015). Thirdly, the Value Proposals Layer, articulated by Reck et al. (2020), emphasizes integration, personalization, and efficient management for superior service quality and customer satisfaction. Lastly, the Infrastructure Layer, discussed by Senn (2020) and Kramers et al. (2018), underscores the technological and organizational backbone supporting MaaS operations. These layers collectively form a robust framework for navigating and optimizing the MaaS ecosystem, ensuring its success and relevance in modern transportation paradigms.

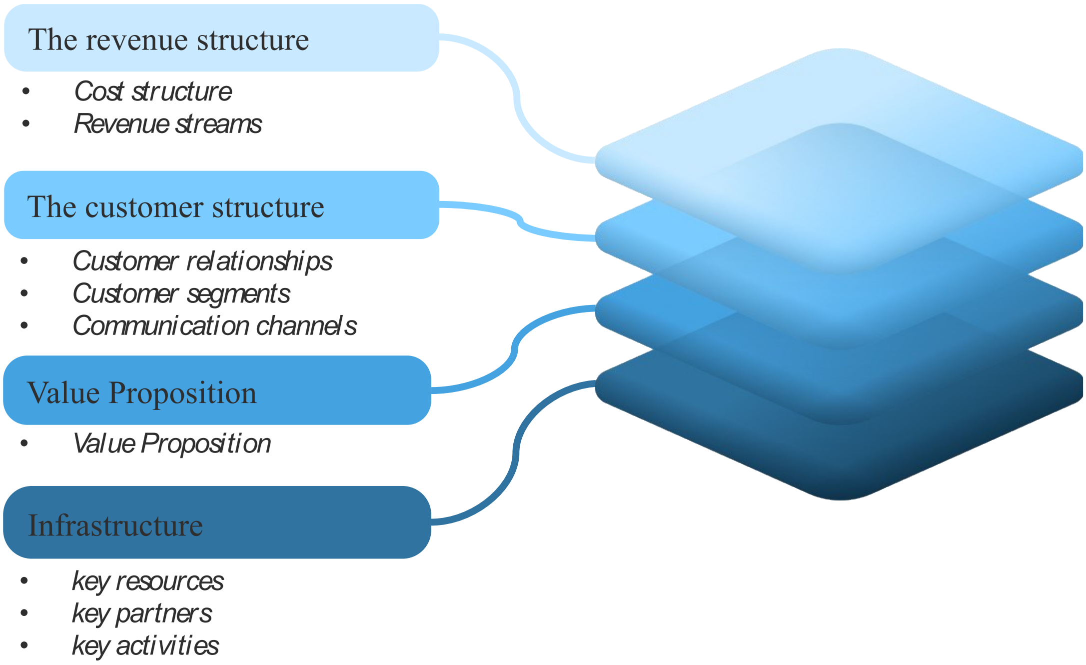

Fig. 14. Illustration of the Four Key Layers of MaaS. Source: The Author.

4.3.1 The Revenue structures.

a) Cost structure

According to Kramers et al. (2018), it is possible to distinguish between investment and operating expenses when it comes to addressing ecological, societal, political, and judicial liabilities. This entails including all vital resources, such as IT infrastructure, application development, fleet procurement and acquisition, and the establishment of a compelling brand within the ambit of investment costs.

b)Revenue streams

In terms of revenue streams, MaaS fares are predominantly classified into two primary categories: pay-as-you-go (time or distance-dependent) and memberships on an annual, monthly, or daily basis that incorporate multiple MaaS packages (Ho, 2022). However, transaction fees are identified as the most significant source of revenue, with such fees potentially consisting of either brokerage-based or fixed-fee costs (Wong & Hensher, 2021). Additionally, customers from non-mobility industries, such as leisure, catering, and tourism, who utilize MaaS portals as a promotional tool may also be required to pay royalties for advertisements and marketing (Pahwa & Starly, 2021).

4.3.2 The Customer Structures.

c) Customer segments

In the domain of MaaS, understanding consumer preferences is important for service providers. Such preferences encompass several attributes like consumer types, mobility, and modality preferences, trip objectives, frequency of travel, spatial dimension, and quasi- and non-mobility service customers (Vij et al., 2013). To gain insights into latent aspects related to the lifestyle and the lifecycle, expressed preference data was integrated and analyzed (Gehrke et al., 2019). The present study adopts this approach and identifies three distinct categories of consumers. The first category includes private vehicle owners and drivers who possess a valid driving license but do not hold a transit pass. The second category comprises dependent transport users who possess both a driving permit and a transit pass. The third category is that of intermodal travelers who occasionally utilize both private and public modes of transportation. By classifying consumers into these categories, MaaS providers can devise targeted strategies to cater to the diverse needs and preferences of different consumer groups.

It is essential to distinguish between private and business customers. Additionally, consumer mobility types are long-term decisions that shape overall travel patterns, while modality modes pertain to immediate transportation choices (Gehrke et al., 2019). Various settings are also considered, including those distinguishing mobility styles (Haustein & Nielsen, 2016), particularly for leisure travel (Lanzendorf, 2002), sustainable traveling behavior (Knieling et al., 2020) (Prillwitz & Barr, 2011), and shared options behavior (Lanzendorf, 2002).

d) Customer relationships

Incorporating customers into transportation services is a powerful way to improve existing services and create new ones. This is done through co-creation, which includes seeking customer feedback, ratings, and social media interactions. These efforts target enhancing the relationship between suppliers and customers, retaining customers, and improving customer service. Personalized, automated customer support and self-service options are fundamental aspects of these services. By using these technologies and approaches, transportation providers can offer exceptional customer experiences, cultivate brand loyalty, and boost their business (Zhu et al., 2017).

e) Customer channels

A wide range of customers and stakeholders can be effectively reached by leveraging diverse communication channels, including sales and customer service staff, newspapers and magazines, and digital platforms such as websites, social media, and mobile apps. By establishing robust and dynamic communication networks, transportation service providers can improve their visibility and reputation in the market (Semanjski & Gautama, 2015).

4.3.3 The Value Proposals

The integration of services, personalization, interconnected transport modes, the range of sharing options, comprehensive service facilities, and efficient database management are pivotal factors that contribute to the success of MaaS models (Reck et al., 2020). These features not only enhance the overall quality of transportation services but also facilitate seamless and convenient travel experiences for customers (Stremersch & Tellis, 2002). Based on the research investigation, MaaS companies leveraging these critical components´ providers could improve the sustainability, efficiency, and profitability of their transportation services while simultaneously enhancing customer satisfaction and loyalty.

4.3.4 Infrastructure

f) Main resources

The underlying components of IT infrastructure in MaaS encompass technological platforms, computing hardware, routing and matching algorithms, application programming interfaces APIs, user and driver applications, trip planners, and electronic payment systems. This category includes data from users and other sources like climate, weather, local events, and social media. It also involves data processing tools and an information management system. Important resources in MaaS are IT infrastructure, data, vehicles, transportation infrastructure, people, and capital. People involved in MaaS can be users or employees of companies, and funding can come from loans or private equity. Vehicles and transportation infrastructure are divided into three groups: automobiles, transportation infrastructure, and refueling or charging infrastructure.

g)Main activities

A categorization of the key activities is made based on external and internal core and supporting actions. The extent of partner integration within the MaaS ecosystem determines whether an activity is internal or external. The level of integration can vary from highly structured to less organized (Senn, 2020).

h) Main Partners

The key partners in the MaaS ecosystem comprise mobility and non-mobility service providers, IT service providers, regulatory agencies, and financial conciliators. IT providers can be further subcategorized into data service providers, GPS and telecommunications companies, legal entities, and payment operators. The mobility providers consist of PT operative cores, private transport operators, transport infrastructure suppliers, Original Equipment Manufacturers OEMs, and peer-to-peer P2P mobility service providers such as P2P carsharing. Non-mobility service providers such as lodging services, events, leisure and entertainment services, and research organizations may become essential partners in the future as MaaS evolves into a multi-service platform. Regulatory organizations play a critical role as MaaS is embedded within a publicly governed mobility system. The level of integration among these partners distinguishes between internal and external activities in the MaaS ecosystem.

4.4 MAAS DATA CLASSIFICATION

In the dynamic landscape of modern business, data assumes a paramount role, permeating every facet of operations, from in-depth market research and sophisticated analysis to fostering meaningful spanning across multiple domains (Turet & Costa, 2022).

In the context of data exploitation strategies, a significant development occurred when Google announced in April 2019 its plans to embark on building the Document Understanding AI[5]. This step marks a pivotal move towards leveraging advanced AI technologies to enhance the understanding and processing of documents. The introduction of Document Understanding AI has the potential to revolutionize information management and document analysis practices across various industries, replete with sophisticated functionalities and tangible applications. Appendix E provides tables detailing the derived data types extracted from the elaborated ecosystem. The following subsections delve into each type, as seen in Fig. 15, distinguishing between structured and unstructured data to clarify the disparities between these data categories.

[5] https://lawtomated.com/google-enters-the-contract-extraction-space/ (Last accessed on 02.2024)

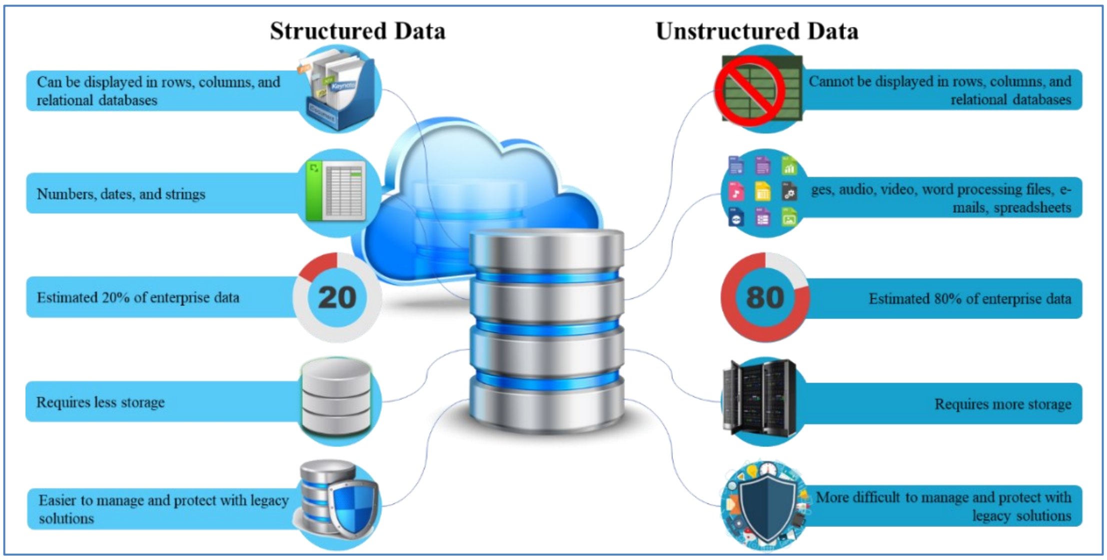

Fig. 15. Structured Data Vs. Unstructured Data. Source: (Abdullah & Ahmad, 2013) Edited by the Author.

a) Structured data

Structured data refers to the type of data that is organized in a specific format or structure, usually in a tabular form, stored in databases that are intricately designed to recognize and establish relationships between the various entities of data being stored. Often, relational database management systems (RDBMSs) are utilized to manage such databases. Fundamentally, a database is visualized as a table comprising rows and columns that store related data. However, it is important to note that diverse forms of databases exist. Structured data presents an exceptional advantage in that it can be labeled, thereby facilitating the effortless identification of its characteristics and interconnections with other data. The labeled nature of this data format makes it easily searchable using manually generated queries or those generated by algorithms. Some examples of structured data in MaaS include:

- User data includes structured data such as user profiles, preferences, and payment information. It can be used to tailor transportation services to individual needs and preferences.
- Transportation data includes structured data such as schedules, routes, and pricing information for various transportation modes. It can be used to optimize travel planning and reduce congestion.

- Performance data includes structured data such as usage statistics, feedback, and ratings for various transportation services. It can be used to improve the quality of services and enhance the overall user experience.
- Financial data includes structured data such as revenue, expenses, and profit margins for MaaS operators and transportation service providers. It can be used to evaluate the financial viability of MaaS platforms and optimize pricing strategies.

b) Unstructured Data

Unstructured data refers to data that does not have a predefined structure or format and cannot be easily organized into a database or table. It refers to any form of digital information lacking an established organization and labeling system to denote meaningful interrelationships among its constituent elements. In other words, this type of data, while still possessing a fundamental configuration comprised of bits and bytes, remains devoid of any clear structure to facilitate optimal storage, retrieval, and utilization. The Common types of machine-generated unstructured data include Satellite imagery (weather data, geographic and topographic forms), Scientific data (oil and gas exploration, maritime exploration, seismic imagery, and atmospheric data), and Digital surveillance (CCTV).

MaaS data include all the previously mentioned data on movements, routing, and trajectory derived generally from cell phone networks and GPS data used by individuals, connected vehicles, and navigation systems. IoT sensors, conventional interchange calculation spots, Wi-Fi/ Bluetooth vehicle counters, and cameras with recognition systems. GIS-based data, such as location indicators, and static and dynamic geospatial data, such as road geometry and layout, Points of Interest PoIs, EV stations, road closures, and traffic density. Public transit data: real-time streaming of PT timetables, vehicle locations, location, and count of mobility modes at public transit stations. Transportation policies and documents issued by the transportation department and the local authorities on traffic regulations and the implementation of new orders. Environmental data regarding the emissions, air quality, and carbon level estimation, as well as the weather data, including temperature, precipitation, wind, flooding, etc., the Socioeconomic data, in particular the geodemographic data and behavioral analysis, social activities, and the features of local communities.

Transaction data from booking, different payment methods, ticketing, and subscriptions for different mobility services.

4.5 CITY PLANNING DATA INTEGRATION

In attempting to realize sustainability, fairness, and economic feasibility in urban planning, it is important to embrace optimal approaches. To this end, the SDGs and the smart city concept, as explicated by Blasi et al. (2022), offer a comprehensive and holistic set of goals and principles that can serve as a guide for such practices. Both frameworks can guide city planners looking to develop best practices for city planning.

4.5.1 SDGs and city planning

In 2015, the United Nations embraced the SDGs as a comprehensive collection of global objectives. Their overarching objective is to chart a course towards a better and more sustainable future for humanity. For city planning initiatives, the SDGs can serve as a blueprint for steering urban development toward sustainability, equity, and economic viability. Thus, their incorporation into urban planning frameworks can promote prudent decision-making while fostering the creation of vibrant, inclusive, and resilient cities.

The utilization of the SDGs in city planning practices presents an array of advantages. Primarily, the SDGs proffer an exhaustive and all-encompassing set of objectives, enabling cities to tackle multifarious predicaments ranging from environmental sustainability and economic progress to social inclusivity and human welfare (Grossi & Trunova, 2021). By adopting the SDGs as a guiding framework, city planners can guarantee that their developmental schemes are founded on the requirements of all community members (Papadopoulou, 2021).

Of paramount importance, the SDGs are predicated on the notion of mutual reinforcement and indivisibility, meaning that advancements in one domain can catalyze progress in other fields (Ravn Boess et al., 2021). Considering, for instance, the reduction of pollution and the amelioration of air quality. Not only can these measures improve public health, but they can also foster economic development and curtail healthcare expenses (Carr et al., 2021). This can enable urban planners to prioritize their endeavors and optimize the use of limited resources to effectuate tangible progress. Furthermore, the SDGs engender common parlance and framework that can foster communication and collaboration among diverse stakeholders, including local administrations, corporations, civil society organizations, and inhabitants (Cole & Broadhurst, 2021). This can engender consensus-building and support for urban planning initiatives and guarantee the efficient and effective implementation of development plans.

Considering these salient attributes, the SDGs emerge as a powerful toolset for urban planners, offering a clear and comprehensive objective that can shepherd the construction of sustainable, equitable, and financially viable cities.

4.5.2 Smart city concept and city planning

The notion of a smart city entails the implementation of technology and data-driven solutions to elevate the standard of living of inhabitants while boosting the efficiency of urban systems. This concept holds fundamental significance in the context of city planning for several reasons:

First, the use of technology and data-driven solutions helps city planners to make more informed decisions about the development of the city. By gathering and analyzing data on a wide range of factors, such as population density, traffic patterns, and public services, city planners can identify trends and patterns that can inform the development of more effective and efficient city plans.

Second, concretizing the smart city model helps city planners to engage with residents and other stakeholders more effectively in the planning process. By using online platforms and tools, city planners can gather feedback and input from a wider range of people and thus provide real-time updates and information about city planning initiatives.

Third, the implication of the notion of a smart city also assists in improving the efficiency and sustainability of urban systems. For example, smart transportation systems help to decrease traffic congestion and air pollution, while smart energy systems reduce greenhouse gas emissions and improve the resiliency of the city to climate change.

The concept of a smart city is important for city planning by providing a framework for using technology and data-driven solutions to improve the quality of life for residents and enhance the efficiency of urban systems.

4.5.3 The convergence between SDGs & smart city concept

The convergence or the synergistic correlation between smart cities and the SDGs is grounded on the premise that the advancement of smart urbanization can furnish a salient framework to raise and drive the achievement of the SDGs. This convergence is hinged upon the overarching concept that the assimilation of technology and data-centric resolutions in urban planning and governance facilitates the remediation of multifarious challenges and objectives preserved in the SDGs. Indeed, the integration of innovative technology and data-driven solutions into city planning can invigorate and bolster sustainable development, amplify the effectiveness of public services, and augment the quality of life of urban residents. Consequently, this union between smart cities and the SDGs means a promising future for the realization of the aspirations of the 2030 Agenda for Sustainable Development.

For example, the use of smart transportation systems to reduce greenhouse gas emissions and improve air quality contributes to SDG 13 (climate action) and SDG 3 (good health and well-being). The use of smart energy systems increases the use of renewable energy and reduces energy consumption, contributing to SDG 7 (affordable and clean energy) and SDG 11 (sustainable cities and communities). The use of smart governance systems improves transparency and accountability, contributing to SDG 16 (peace, justice, and strong institutions).

In addition, the development of smart cities supports the achievement of many other SDGs, including those related to economic development, social inclusion, and environmental sustainability. By aligning city planning with the SDGs, cities ensure that their development plans are sustainable, equitable, and economically viable and that they support achieving global goals.

The convergence between smart cities and SDGs in the literature is still in its infancy, and many studies have attempted to smarten sustainable development in cities or bolster smart cities and SDGs (Blasi et al., 2022). In the present research, a thorough analysis of the prevalent literature is conducted utilizing NLP to discern the most employed terminologies. The results reveal that the areas of Sustainability, Resource Management, Governance, Innovation, and Collaboration emerge as the shared focal points between these two literary disciplines, see Table 3. Significantly, these thematic clusters are identified as the primary domains of interest, serving as the targeted framework for the subsequent data extraction from MaaS data.

Table 3. City Planning Domains from Smart City and SDGs Relevant Keywords

Keyword	Relevance
Sustainability	0.429622
Resource Management	0.392940
Governance	0.364287
Innovation	0.314509
Collaboration	0.312953

4.5.4 City planning domains of application for MaaS data.

a) **Sustainability** is at the core of the SDGs and the smart city concept. The SDGs are designed to be a blueprint for achieving sustainable development, with specific goals and targets related to environmental sustainability, economic development, and social inclusion.

Similarly, the development of a smart city is based on the idea that technology and data-driven solutions can support sustainability by improving the efficiency of urban systems, reducing greenhouse gas emissions, and enhancing the city's resilience to climate change. Sustainability is a key principle underlying the SDGs and the smart city concept.

b) **Resource management** is a critical aspect of sustainable development and is closely related to the SDGs and the smart city concept.

In the context of the SDGs, resource management is relevant to several of the global goals, including SDG 7 (affordable and clean energy), SDG 12 (responsible consumption and production), and SDG 13 (climate action). These goals outline specific targets for efficient use of natural resources, reducing waste and pollution, and transitioning to a low-carbon economy.

In the context of a smart city, resource management is also an important consideration. Technology and data-driven solutions can support the efficient and sustainable use of resources by providing real-time information about resource use and optimizing resource allocation. For example, smart energy systems can help to reduce energy consumption and increase the use of renewable energy, while smart waste management systems help to reduce waste and improve recycling rates.

c) **Governance** is a critical aspect of sustainable development and is closely related to the SDGs and the smart city concept.

In the context of the SDGs, governance is relevant to several of the global goals, including SDG 16 (peace, justice, and strong institutions), SDG 17 (partnerships for the goals), and SDG 5 (gender equality). These goals outline specific targets related to the promotion of good governance, the strengthening of institutions, and the empowerment of women and girls.

In the context of a smart city, governance is also an important consideration. Technology and data-driven solutions can support good governance by enabling greater transparency and accountability and providing citizens with greater access to information and participation in decision-making processes. For example, smart governance systems can help improve government processes' transparency and efficiency and enable citizens to access public services and information online.

d) **Innovation** is an important driver of sustainable development and is closely related to the SDGs and the smart city concept.

In the context of the SDGs, innovation is relevant to several of the global goals, including SDG 9 (industry, innovation, and infrastructure), SDG 7 (affordable and clean energy), and SDG 8 (decent work and economic growth). These goals outline specific targets related to the promotion of innovation, the development of modern technologies, and the creation of decent jobs and economic opportunities.

In the context of a smart city, innovation is also a key consideration. Developing a smart city requires innovative technologies and data-driven solutions to improve the quality of life for residents and enhance the efficiency of urban systems. For example, the use of smart transportation systems can improve the efficiency of urban mobility, while the use of smart energy systems can support the transition to renewable energy.

e) **Collaboration** is an essential aspect of sustainable development and is closely related to both the SDGs and the concept of a smart city.

In the context of the SDGs, collaboration is relevant to several of the global goals, including SDG 17 (partnerships for the goals), SDG 11 (sustainable cities and communities), and SDG 16 (peace, justice, and strong institutions). These goals outline specific targets related to the promotion of partnerships and collaboration, the development of inclusive and sustainable cities, and the strengthening of institutions.

Collaboration is also a critical consideration in the context of a smart city. Developing a smart city requires the participation and input of a wide range of stakeholders, including local governments, businesses, civil society organizations, and residents. By fostering collaboration and partnerships among these stakeholders, cities can ensure that their development plans are inclusive and reflect the needs and priorities of the community.

4.6 NATURAL LANGUAGE PROCESSING MODEL

With respect to the research parameters defined in this research, the significance of NLP is intricately connected to the vast quantities of data. The data collected, stored, and processed within the research database is expressed in a natural human language. However, the manual processing of such data is neither effective nor efficient, as it may require a long time and much effort to accomplish. Thus, this part of the research explains the working principle of NLP and explores its capabilities.

NLP uses two main techniques: syntax and semantic analysis.

a) *Syntax* is the placement of words, clauses, or sentences to ensure proper grammar, and it is the examination of how phrases are put together and how their elements interact. NLP analyzes syntax to determine a language's meaning based on grammatical rules. Syntax methods comprise:

- ✓ **Parsing** is the breaking down of a phrase into its constituent pieces and explaining their syntactic functions or the examination of a statement's grammar. If the text "The bus departed" is supplied to an NLP system as an example, this statement must be broken down into its constituent components to be parsed. For instance, the bus is a noun, while departed is a verb. Although it is a simple technique, its usefulness can be greatly extended to the more intricate and demanding downstream processing tasks.
- ✓ **Word segmentation** is the process of extracting words and string formations from a text sequence. If someone scans a handwritten paper into a computer, for instance, the program can detect the white or free spaces in the text and

define them as gaps in the scanned page. Languages with plenty of compound words must decompound them.

- ✓ **Sentence breaking:** Set up sentence breaks in lengthy paragraphs. Example: if the following sentence is supplied into an NLP system, "The bus departed. I arrived there." The sentence breaking used by the algorithm is meant to define and recognize the period of the event's occurrence.
- ✓ **Morphological segmentation** breaks down words into smaller components known as lexemes or morphemes. As an illustration, the algorithm would convert the word "unreliably" into [[un[[rely]able]]ly, where "un," "rely," "able," and "ly" are all recognized as morphemes. Voice recognition, instant translation, and similar programs benefit greatly from this.
- ✓ **Stemming** separates words with nuances into their corresponding root forms by removing the suffix and reducing it to its root word. The algorithm can identify the word "departed" in the phrase "The bus departed" as having the root "depart." This would be helpful if a user were searching a document for every occurrence of the term depart and all its verb forms. Even when the characters are different, the program can still state that they are fundamentally the same word.

b) *Semantics* is the exploration of how words are used and what they imply. It is a division of linguistics and logic that dissects meaning. Its algorithms are used in NLP to comprehend sentence structure and meaning. Semantic methods consist of:

- ✓ **Word sense disambiguation** determines a term's meaning depending on context. For example, if the phrase "The bike is in the pen." Is taken there are several meanings for the word pen. This approach enables an algorithm to recognize that the term "pen" in this context refers to a fenced-in space rather than a writing tool. Three broad categories are used for this technique: The supervised, unsupervised method, and the knowledge-based approach.
- ✓ **Named Entity Recognition NER,** entity chunking, entity extraction, and entity identification are other labels for NER. It searches for and organizes certain items in a set text or document corpus as part of information extraction (IE). NER specifies the groupings of words that can be used. Using this technique, an algorithm may examine a news story and find any references for the nature of the expression. It can characterize items that seem the same using

the semantics of the text. As an illustration, in the statement “Daniel Station's son went to the station and rented a bike,” the algorithm might identify the two expressions of "station" as two distinct things, the first one being a person and the second being a location,

- ✓ **Natural Language Understanding NLU** employs AI to interpret the received data. It can be undertaken in a way that the written words might be transformed into something meaningful in the natural language. NLU extracts the intelligible meaning from texts. It was developed together with voice recognition and utilized to convert spoken words into written words, regardless of whether the text includes errors and mispronunciations.

The NLP approach developed for this study is based on DL, with AI to examine and use the data patterns. Massive volumes of labeled data are necessary for DL models so that the NLP algorithm trains them and finds pertinent connections. Constructing the big data set is one of the foremost hurdles of the NLP implementation for this research.

While a rule-based approach is suitable for specific and well-defined tasks, the DL approach offers a more dynamic and versatile solution to processing natural language data. By leveraging the power of ML and neural networks, the present study enables the adaptation of new patterns and variations in the data, leading to more accurate and comprehensive analysis. Thus, the DL approach is a critical tool in advancing the results, enhancing the findings, and unlocking the full potential of the NLP.

In the realm of this research, the practice of mining crucial information from a corpus of texts or sentences is achieved through the utilization of Rapid Automatic Keyword Extraction (RAKE). RAKE is an automated process that selectively extracts the most pertinent keywords from the input text. By implementing the previously described techniques, the automated extraction of the most salient words from the injected data is made possible. This methodology serves the objective of identifying the crucial topics embedded within the MaaS operational ecosystem.

In the upcoming sections, an in-depth exploration of the operational process and technical aspects will be expounded upon.

4.6.1 NLP implementation process

The incorporation of NLP in this research involves two primary phases, namely data pre-processing and algorithm creation and deployment. The pre-processing stage involves preparing and refining text data for computer-based analysis. Text features are first identified, after which Tokenization is applied to segment the text into smaller units. Stop word elimination is then employed to eliminate all non-distinctive and non-informative keywords from the content. Lemmatization and stemming techniques are also applied to establish and preserve the root form of words for optimal processing. Moreover, Part-of-Speech Tagging (PoST) is utilized to identify and assign a particular part of speech to a term in the text corpus, depending on both its definition and context. Upon completion of the data pre-processing stage, the library is selected, and accordingly, the algorithm is developed to process the refined data.

Conventionally, discourse integration and pragmatic analysis are the last two stages of the NLP implementation. However, since they focus more on the communicative and societal content and allude to the feeling of context, they are not considered for this study.

The selection of NLP library for enhanced text processing

In the realm of NLP, a plethora of tools and resources are available to facilitate the processing and analysis of textual data. Notably, some of the prominent tools suited for NLP applications include the Natural Language Toolkit (NLTK), Gensim, and Intel Natural Language Processing Architect.

- NLTK, a renowned open-source Python module, stands out for its comprehensive collection of datasets and configurations, making it a good resource for a wide range of NLP tasks. Its user-friendly interface and extensive documentation have made it a preferred choice across various research domains.
- Gensim, another Python library, finds its niche in tasks like topic modeling and document indexing. Its array of features, including similarity inquiries, semantic analysis, and text summarization, positions it as an asset for NLP applications.
- Intel NLP Architect, a Python library, offers deep learning topologies and techniques tailored for NLP tasks. It provides a user-friendly interface that

simplifies the development and deployment of deep learning models in the field of NLP, catering to both researchers and practitioners.

For this study, SpaCy, an advanced and open-source NLP library available for Python, has been chosen. SpaCy's reputation rests on its speed, efficiency, and ease of use. It excels in various NLP tasks, including the recognition of named entities, dependency parsing, topic modeling, and part-of-speech tagging.

The selection of SpaCy for this study is underpinned by its exceptional performance in these tasks, aligning perfectly with the study's goal of processing and comprehending textual information within the context of city planning and MaaS.

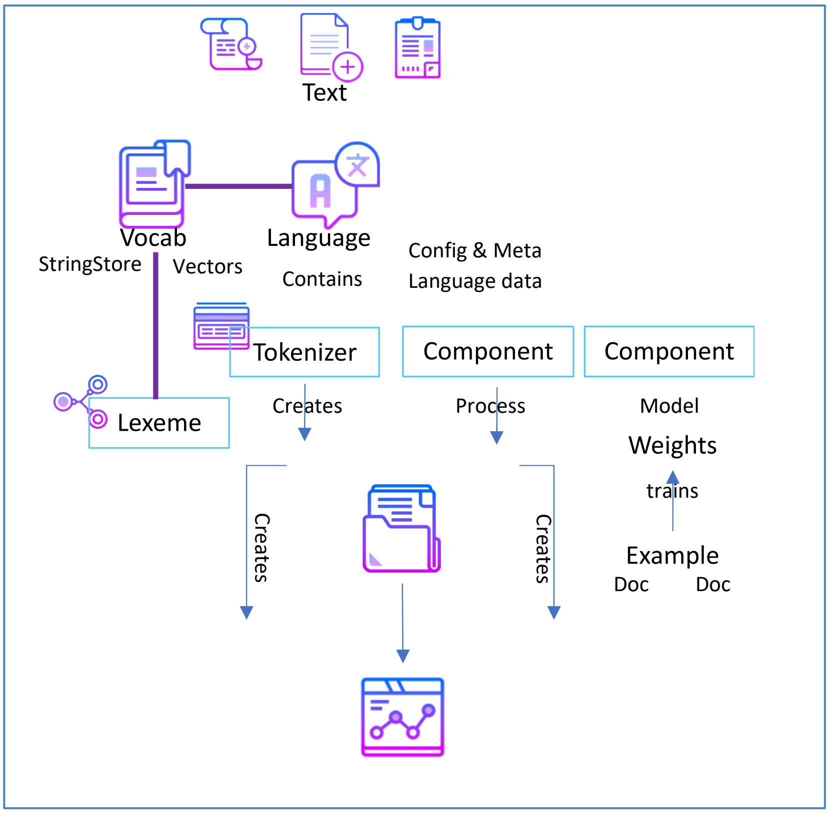

Fig. 16. The central data structures in SpaCy. Source: spacy.io

The central data structures in SpaCy are the **Doc**, **Token,** and **Span** objects, see Fig. 16. A **Doc** object is a sequence of tokens representing a text. Each **Token** object contains information such as its position in the **Doc**, its text value, and various linguistic annotations such as part-of-speech tags and named entities. A **Span** object is a slice of the **Doc** that consists of one or more contiguous **Tokens**.

SpaCy's architecture consists of a pipeline of modular components that process the text and enrich the **Doc** with linguistic annotations. The pipeline typically includes tokenization, part-of-speech tagging, dependency parsing, named entity recognition, and more. Each component takes a **Doc** object as input, adds its annotations, and passes the **Doc** to the next component in the pipeline.

4.6.2 Data Pre-Processing

The preliminary stage in developing any ML-based solution is pre-processing the data. The data sources undergo preliminary processing in the present study by employing the Python packages Scrapy and PyPDF2, which efficiently cater to websites and documents, respectively. Furthermore, the entirety of the typescript is subsequently transformed into the SpaCy document object, utilizing code 01 in 1)a)Appendix E as the means to this end. Once this transformation is complete, the keywords within the text are subjected to a corresponding vector transformation, enabling the selection of related keywords through cosine similarity. The second code in 1)a)Appendix E serves as a pivotal reference point for executing this task, ensuring the successful realization of the objectives set forth. Thus, by virtue of the aforementioned practices, the study attains high accuracy and precision, which is indispensable for attaining reliable and trustworthy results.

4.6.3 Processing pipeline

As previously elucidated, the invocation of pipeline components is conducted on the **Doc**, see Fig. 17. Notably, the tokenizer is executed before the components. It is worth highlighting that these components can be supplemented by means of integration, which may encompass the incorporation of a statistical model alongside its respective trained weights or, alternatively, the implementation of solely rule-based modifications to the **Doc**. Within this context, it is important that SpaCy provides a diverse array of pre-existing components that cater to various language processing tasks. Moreover, it affords the flexibility of incorporating bespoke components to cater to unique processing requirements.

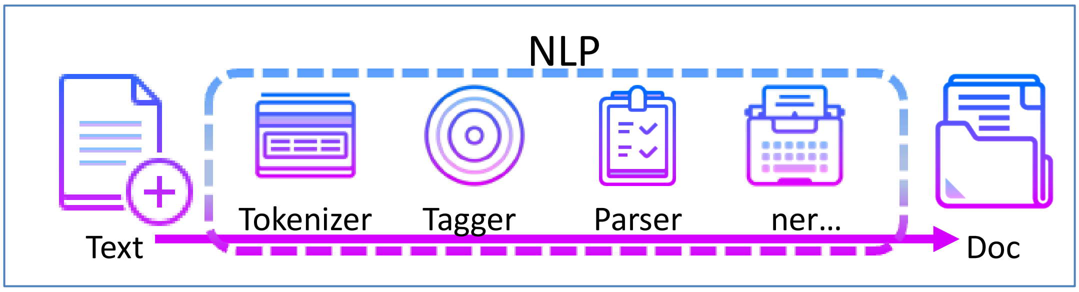

Fig. 17. Processing Pipeline and its Components. Source: spacy.io

At this stage, the extraction of information from `Doc` objects is facilitated, predicated on match patterns that accurately depict the sequences, classified as MaaS data. It effectively operates on the `Doc` object and enables accessibility to the tokens that correspond to the identified matches, thereby laying the foundation for subsequent processing steps.

In this chapter, important data was collected, and the MaaS systems' organization was examined. The MaaS ecosystem and various data types were explored and compared with the NLP processing approach. This chapter laid the foundation for the model to generate the outlined outputs targeted by this study. In the next chapter, the results of the model analysis will be presented and explained.

Chapter 5: Results

This chapter delves into MaaS data sources, closely examining the attributes of MaaS companies and their integration levels while also exploring their ties to urban planning. Through this study, new patterns, relationships, and insights were discovered in section 5.1. Building on the preceding chapters, the outcomes of MaaS data analysis are presented in section 5.2, starting with the unveiling of findings derived from the NLP approach. These inputs are then juxtaposed with city planning data to gauge the relevance of MaaS data in urban planning practices, involving the assessment of the frequency and significance of each domain. In the second iteration of the study, a more refined process approach is introduced, and a larger dataset is utilized, the enhanced aspects of which are explained in section 5.3. Section 5.4 focuses on the results of the second iteration, followed by the use cases derived from this stage in section 5.5.

5.1 MAAS ORGANIZATIONS AND THEIR FEATURES

The examination of the starting year, as well as the public or private status and level of integration of MaaS companies, forms a component of this part of the research. This segment of the investigation builds upon the analysis of the MaaS market's evolution, which accentuates the ascendance of private enterprises and the growing participation of public entities in the sector. The examination of the degree of collaboration between public and private organizations offers further illumination into how these entities work to devise mobility solutions that cater to the demands of both citizens and the city. Moreover, this scrutiny plays a pivotal role in identifying patterns in the integration of MaaS firms in the urban system, which is instrumental in comprehending how to harness MaaS data for urban planning applications.

5.1.1 The role of public and private operators in MaaS development

Since this study aims to evaluate the relevance of MaaS data, it analyzes 200 MaaS organizations, 170 of which are private companies and 30 are public entities under government authority. Public actors, who hold a monopoly position, are known to ensure that mobility solutions cater to not only citizens' needs but also the city's objectives. Meanwhile, MaaS private operators are required to share non-sensitive user data for city or traffic planning purposes and achieve a specific conversion rate.

Incentives such as benefits for shifting to off-peak public transportation trips must also be provided to users. Fig. 18 depicts the mapping of these corporations, their type as private or public per year of creation. The analysis of the data reveals a consistent upward trend in the number of MaaS companies over the years. Notably, there was a substantial surge in their creation during the years 2017 and 2018. Predominantly, the dataset consists of privately owned MaaS companies, constituting the majority, whereas a minority of companies fall under the public ownership category.

Delving into the year of establishment perspective, the years 2007 and 2008 exclusively saw the creation of private MaaS companies, with no public counterparts during that period. However, a pivotal shift occurred in 2009 when the first public MaaS companies came into existence. 2015 marked a significant increase in the number of public MaaS companies as three new entities entered the market. This trajectory continued to evolve until 2019, witnessing the emergence of eight new public MaaS companies during that year. Remarkably, 2017 stands out as the year with the highest influx of new MaaS companies, with a remarkable total of 26 such companies established.

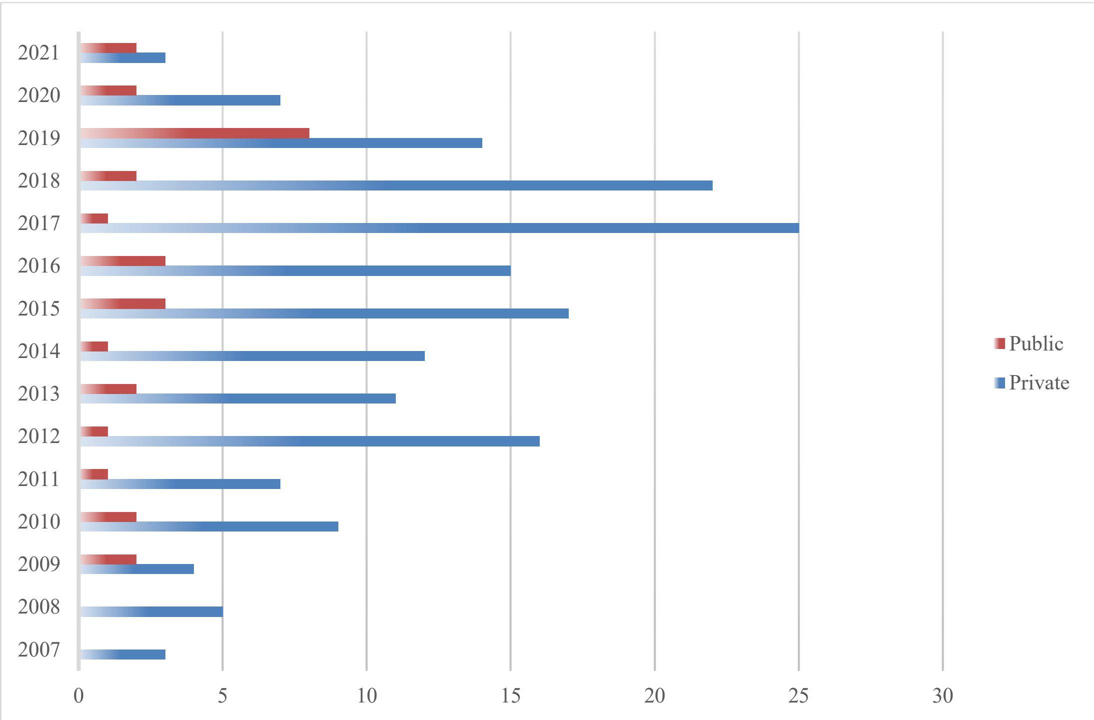

Fig. 18. Annual Enumeration of Public and Private MaaS Companies 2007-2021. Source: The Author.

This temporal analysis underscores the dynamic nature of the MaaS industry, with distinct phases characterized by shifts in the proportion of public and private entities entering the market.

Table 4 shows the results of the independent samples t-test comparing private and public MaaS companies based on their integration level. The integration level is categorized as low (1), medium (2), and high (3).

Table 4. Group Statistics for Privat Vs. Public MaaS Organizations.

	Type	N	Mean	Std. Deviation	Std. Error Mean
Integration Level	Private	170	2,41	,825	,063
	Public	30	2,30	,750	,137

The mean integration level for the private group is 2.41, with a standard deviation of 0.825 and a standard error of the mean (SEM) of 0.063. For public companies, the mean integration level is 2.30, with a standard deviation of 0.750 and an SEM of 0.137.

Table 5. Independent Samples Test for Privat Vs. Public MaaS Organizations.

		Levene's Test for Equality of Variances		t-test for Equality of Means	
		F	Sig.	t	df
Integration Level	Equal variances assumed	1,538	,216	,657	198
	Equal variances not assumed			,702	42,382

In Table 5 Levene's Test for Equality of Variances assesses whether the variances of the two groups are equal. When variances are equal, it is assumed that both groups have similar variability. The F-statistic for this test is 1.538, with a p-value of 0.216. Since the p-value is greater than 0.05 (common significance level), the null hypothesis is not rejected; see sub-section 3.6.1. This suggests that there is **no statistically significant difference** in variances between the two groups. In other words, the assumption of equal variances is reasonable.

When assuming equal variances, the t-statistic is 0.657 with 198 degrees of freedom. The p-value associated with this test is greater than 0.05. Therefore, when assuming equal variances, there is no statistically significant difference. When not assuming equal variances, the t-statistic is 0.702 with 42.382 degrees of freedom. The p-value is also greater than 0.05. Therefore, even when not assuming equal variances, there is no statistically significant difference in the mean integration levels between the two groups. Thus, based on the data collected in this study, there is no robust evidence to suggest that there is a statistically significant difference in the mean integration levels between private and public companies.

The direction of the statistical relationships found in the comparison between private and public MaaS organizations suggests that, on average, there is no substantial disparity in integration levels between the two types of entities. While the mean integration level for private MaaS organizations slightly exceeds that of public MaaS organizations (2.41 versus 2.30), this difference is not statistically significant. Additionally, the standard deviation, which reflects the variability of integration levels within each group, is relatively similar between private and public organizations, indicating consistent levels of variation in integration across both sectors. The lack of significant difference in integration levels persists even when accounting for potential variations in variances between the groups, as indicated by the non-significant p-values in Levene's test and the t-tests. Therefore, the statistical relationships suggest that, in the context of this study, the nature of ownership (private versus public) does not exert a discernible impact on the level of integration within MaaS organizations.

5.1.2 Unveiling the dynamics of MaaS integration levels

The degree to which MaaS systems are integrated is a key factor that directly influences their capacity to deliver a seamless, end-to-end user experience, which is a vital support for societal and sustainable development goals. This study conducts an analysis of the MaaS integration level based on the assembled dataset segmented by their integration level (high, medium, and low).

Upon examining the data and examining Fig. 19, some insights can be derived. Firstly, the majority of MaaS companies in this dataset boast an elevated level of integration, which translates to them providing a broad spectrum of transportation modes and services. However, there is a substantial number of companies that exhibit a medium and low level of integration. Secondly, the number of MaaS companies with elevated levels of integration has been consistently higher compared to those with medium and low levels of integration.

Intriguingly, the study reveals that all the established MaaS companies in 2007 were characterized by a high level of integration, but the trend shifted in 2009 when MaaS companies still had a low level of integration. Furthermore, in 2017, a total of 15 new MaaS companies emerged with a high level of integration, while in 2018, seven new MaaS companies emerged with a medium level of integration. Finally, in 2021, all the newly established MaaS companies displayed either medium or low levels of integration.

Overall, this part of the analysis unveils that the MaaS industry is constantly evolving, with companies adapting their integration levels depending on the market they cater to. It also highlights the crucial importance of MaaS integration levels in delivering a seamless and sustainable user experience while accentuating the ongoing dynamic nature of the MaaS industry. Nevertheless, it is observed that the establishment year does not influence the level of integration.

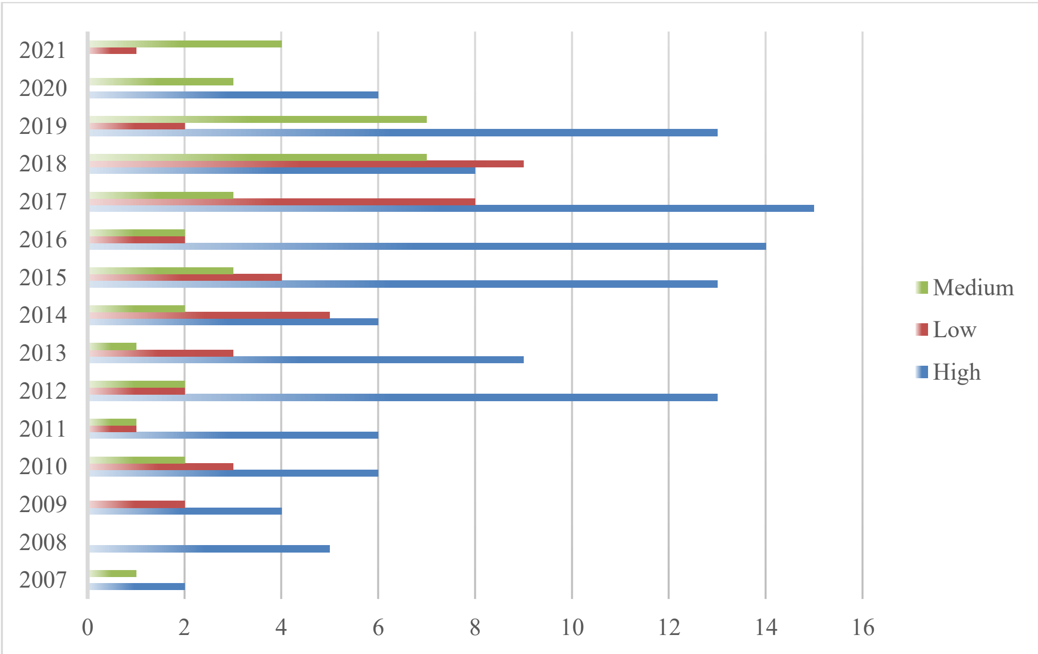

Fig. 19. Assessment of Integration Levels Among MaaS Companies Based on the Year of Creation. Source: The Author.

Table 6 and Table 7 show the results of two chi-square tests conducted to assess the relationship between the number of years since the establishment of a MaaS company and their integration level.

Table 6 compares the integration levels of MaaS companies with the number of years since their establishment: Rows represent Integration Level Low, Medium, and High. The columns represent the number of years since establishment distributed over 2, 3, 4, 5, 6, 7, and 8 years. The counts in each cell represent the number of companies falling into each combination of integration levels and years since establishment.

Table 6. Integration Level Vs. Year Since Establishment

Integration Level	Year						
	-2	3	4	5	6	7	+8
Low	1	0	2	9	8	2	4
Medium	4	3	7	7	3	2	3
High	0	6	13	8	15	14	13
Total	5	9	22	24	26	18	20

In Table 7, the Pearson Chi-Square value is 7.159 with 2 degrees of freedom and an asymptotic significance (two-sided) of 0.028. This test assesses whether there is a statistically significant association between Integration Level and Year Since Establishment. The p-value (0.028) is less than the typical significance level of 0.05, suggesting that **there is evidence of an association**.

The likelihood Ratio value is 6.239 with 2 degrees of freedom and an asymptotic significance (two-sided) of 0.044. Like the Pearson test, it also suggests **a statistically significant association**, though it has a slightly higher p-value.

Linear-by-Linear Association Test checks for a linear association between Integration Level and Year Since Establishment. The value is 0.432 with 1 degree of freedom and a significance of 0.511, which is **not statistically significant**.

Based on the results of Table 7, there appears to be **a statistically significant association** between Integration level and the number of years since establishment, especially according to the Pearson and Likelihood Ratio tests.

The results of the chi-square test indicate a statistically significant association; this suggests that the level of integration is not independent of the number of years since a company's establishment, and there is a meaningful relationship between these two variables.

Table 7. Chi-Square Tests for Assessing the Number of Years since the Establishment Vs. Integration Level.

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	43,334[a]	28	,032
Likelihood Ratio	47,194	28	,013
Linear-by-Linear Association	2,776	1	,096
N of Valid Cases	200		

In this case, the calculated p-value from the chi-square test is 0.032. This suggests that there is evidence to reject the null hypothesis established in sub-section 3.6.2, indicating that there is a **statistically significant association** between the number of years since the creation of MaaS companies and their integration levels based on the data of this study.

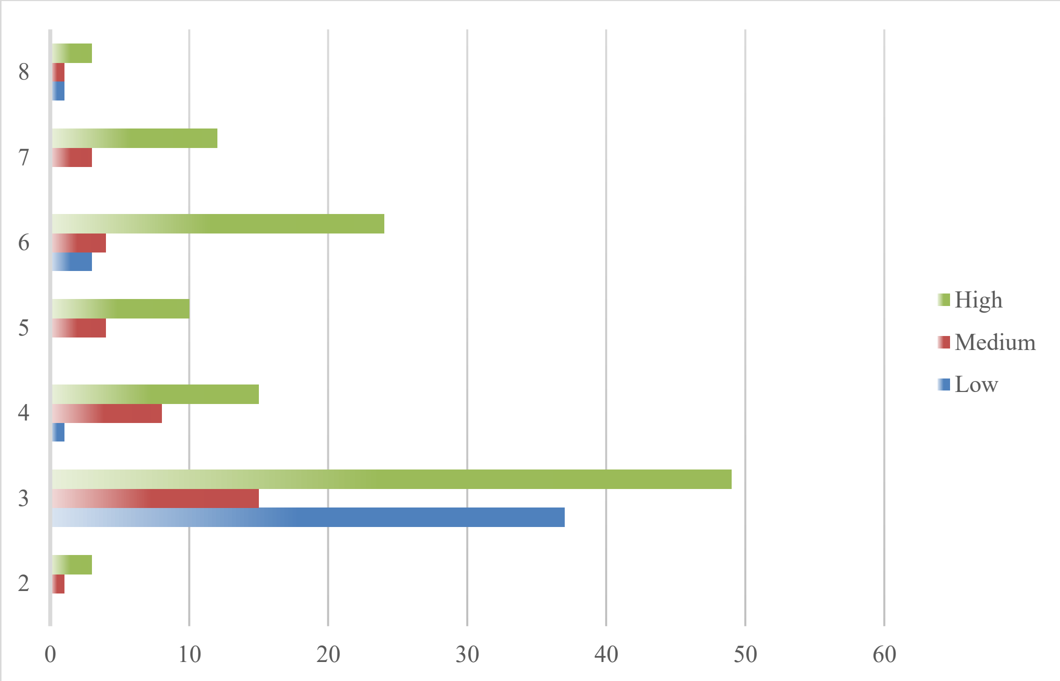

Fig. 20. Number of Mobility Modes Provided and the Level of Integration of MaaS Companies, Source: The Author.

Table 8. Integration Level Vs. Number of Mobility Modes Provided.

Integration level	Number of mobility modes						
	2	3	4	5	6	7	8
1	0	37	1	0	3	0	1
2	1	15	8	4	4	3	1
3	3	49	15	10	24	12	3
Total	4	101	24	14	31	15	5

Table 8 shows the results of a chi-square analysis to examine the relationship between the number of mobility modes a MaaS company provides and the integration level of these services (low, medium, and high).

Each cell in Table 8 represents the count of companies falling into a specific combination of integration level and the number of mobility modes. Rows with the Integration and Columns with the number of modes, ranging from 2 to 8.

Here is a breakdown of the table:

For the low integration level, 37 cases had three modes, 1 case had four, 3 cases had six, and 1 case had eight mobility modes. There were no cases with two, five, or seven mobility modes for integration level 1.

For the medium integration level: 1 case had two mobility modes, 15 cases had three mobility modes, 8 cases had four mobility modes, 4 cases had five mobility modes, 4 cases had six mobility modes, 3 cases had seven mobility modes and one case had eight mobility modes.

For the high integration level: 3 cases had two mobility modes, 49 cases had three mobility modes, 15 cases had four mobility modes, 10 cases had five mobility modes, 24 cases had six mobility modes, 12 cases had seven mobility modes, and 3 cases had eight mobility modes.

Chi-Square Tests: The chi-square tests are used to determine if there is a statistically significant association between integration level and the number of mobility modes provided, see Table 9. Here are the results of the chi-square tests:

1. **Pearson Chi-Square**: the chi-square statistic is calculated using the Pearson method. The value of this statistic is 35.917 with 14 degrees of freedom (df). The p-value is approximately 0.001. In this case, the p-value is small, indicating that there is **a statistically significant association** between integration level and the number of mobility modes provided.
2. **Likelihood Ratio**: This is another chi-square statistic calculated using the likelihood ratio method. The value of this statistic is 43.386 with 14 degrees of freedom (df). The p-value is 0.000 (essentially 0). Like the Pearson Chi-Square, this result suggests a highly significant association between integration level and the number of mobility modes provided.
3. **Linear-by-Linear Association**: This test assesses the linear relationship between the two variables (integration level and the number of mobility modes). The statistic is 13.718 with 1 degree of freedom, and the p-value is 0.000. This result reinforces the idea that there is a significant linear association between these variables.

In summary, the chi-square tests indicate that there is a **strong and statistically significant association** between the integration level of MaaS companies and the number of mobility modes they provide. This suggests that the two variables are not independent, and the integration level does influence the number of mobility modes offered by these companies.

Table 9. Chi-Square Tests for Assessing the Number of Mobility Modes Vs. Integration Level

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	35,917[a]	14	,001
Likelihood Ratio	43,386	14	,000
Linear-by-Linear Association	13,718	1	,000
N of Valid Cases	200		

The results suggest that both the Pearson Chi-Square and the Likelihood Ratio Chi-Square tests have very small p-values, which means that it is highly unlikely to observe the relationship between integration level and the number of mobility modes by random chance. This provides strong evidence against the null hypothesis established in sub-section 3.6.3.

Therefore, based on the provided data, the chi-square test supports the conclusion that there is a statistically significant relationship between the integration level of MaaS companies and the number of mobility modes they provide.

5.1.3 Analyzing Correlations and Trends of MaaS companies

It is necessary to determine the nature of the data each variable represents before calculating the potential correlation between them. The subsequent data types utilized in this research, presented in Appendix D, can be deduced by examining the given data: Company Name is nominal, Type is nominal, Year of Creation is ratio, Level of Integration is ordinal, and Number of Mobility Modes is ratio. The correlation between Year of Creation and Number of Mobility Modes can be determined using Pearson's correlation coefficient, as they are both ratio data. However, the correlation between the Level of Integration and the other variables must be determined using Spearman's rank correlation coefficient, as the Level of Integration is ordinal data.

Therefore, the correlation between Year of Creation and Number of Mobility Modes can be calculated using Pearson's correlation coefficient, which will yield a value between -1 and 1. A value of -1 indicates a perfectly negative correlation, 0 indicates no correlation, and 1 indicates a perfectly positive correlation. This calculation is performed using the statistical software package R. The correlation between the Level of Integration and the other variables can be calculated using

Spearman's rank correlation coefficient. This calculation will also yield a value between -1 and 1, where -1 indicates a perfectly negative correlation, 0 indicates no correlation, and 1 indicates a perfectly positive correlation.

Here are some insights gathered from the data:

- The Type of Company (private) is not likely to be correlated with any of the other variables in the data set.
- There is a positive correlation between the Year of Creation and the Number of Companies, which suggests that more MaaS companies were created over time until 2017 when the number decreased.
- There is no clear correlation between the Level of Integration (explained in section 4.2) and the Number of Mobility Modes. However, it is worth noting that most companies (more than 80%) are classified as having a high level of integration.
- There is a positive correlation between the number of Mobility Modes and the Year of Creation. This suggests that newer companies are more likely to offer a greater number of mobility options.

These insights suggest that the mobility industry is growing rapidly, with more companies being created over time and offering a wider range of mobility modes. However, it is unclear whether the level of integration is a significant factor in determining the number of mobility modes a company offers. The majority of the companies listed are private, indicating that the MaaS industry is predominantly driven by private enterprises.

5.2 MAAS DATA AND CITY PLANNING -STAGE 01

In this section, the objective is to explore the relationship between data sourced from MaaS companies, derived in section 4.4, and its significance in the context of urban planning and SDGs, explained in section 4.5. using NLP techniques depicted in section 4.6. The expected output and the results will provide perceptions of the potential contributions and implications of MaaS data in achieving urban sustainability and development objectives.

The selection of MaaS organizations in the research phases has been twofold. In the first phase, a sample of 50 MaaS companies was chosen from the MaaS ecosystem and the available data by 2021, as detailed in section 3.5. This initial selection established a foundational understanding of MaaS dynamics. Feedback from presentations at international conferences and events informed the refinement of the research approach. In the subsequent expansion phase (stage 02), the sample size was increased to 200 companies, reflecting a broader spectrum of MaaS practices and perspectives. The expansion sought a more comprehensive view of the MaaS landscape, including various operational models, technological capabilities, and geographical contexts.

At stage 01, 50 MaaS companies were selected and examined within five distinct integration levels, emphasizing alignment with SDG domains. By the end of the pre-processing data, the number of the keywords extracted was 9164; after eliminating the duplicated rows and summing their values, 4933 texts were sorted out from the first filtering to the classifier, 3838 duplicated texts were removed, the final total entry for the analysis is 1095 keyword. Table 10 shows the three most frequently used keywords by order with their domain of application and their degree of relevance.

The most frequently utilized keyword, "App," stems from various sources, including platform usability, user feedback, and satisfaction, as it is the primary interface for accessing MaaS APIs. This keyword aligns closely with the domains of Innovation, Collaboration, and Governance, which are the most pertinent areas for App-related data.

Another frequently occurring keyword is "Map," as users often use MaaS Apps for itinerary recommendations, mobility mode information, and various functionalities like GPS data and route optimization. This keyword is primarily associated with Innovation, Resource Management, and Governance.

Additionally, "Fuel" is a recurring keyword that appears in contexts such as comparing EVs and conventional fuel engines, emissions related to transportation, and fuel consumption estimates. The data related to fuel is particularly relevant to Resource Management, Sustainability, and Innovation.

Table 10. Most Frequently Used Keywords within MaaS Data, First Stage.

Order	**Domain and relevance**			
	keyword	Frequency	Domain	Relevance
1	App	822	Innovation	1,00
			Collaboration	0,71
			Governance	0,67
2	Map	794	Innovation	0.66
			Resource Management	0.48

			Governance	0.35
3	Fuel	763	Resource Management	0.95
			Sustainability	0.93
			Innovation	0.60

The matching of the derived keywords created 17356 matches with different relevance levels (0,1 to 1). Fig. 21 shows the number of each domain according to its relevance to the MaaS. The word innovation is the most relevant to MaaS data, followed by resource management and governance, respectively, while sustainability seems to be the least frequent.

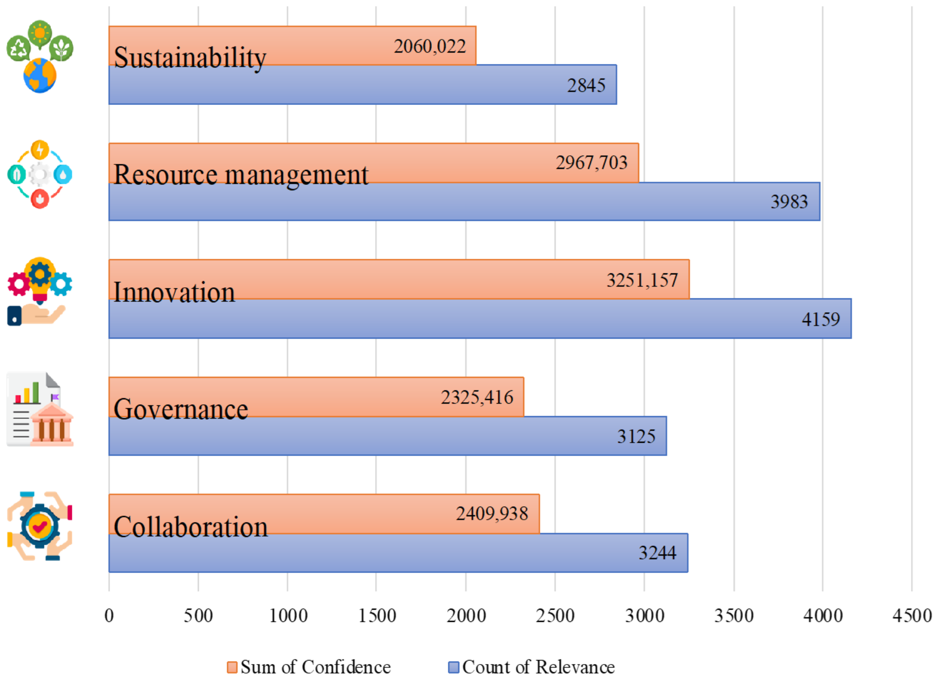

Fig. 21. The Relevant MaaS Data to the City Planning Domains, First Stage. Source: The Author.

The results indicate a significant amount of data relevance and confidence scores across various city planning and SDGs domains.

- **Collaboration**: The Collaboration domain shows a count of 3,244 instances with a cumulative confidence score of 2,409.938. This indicates that MaaS data contains substantial information on collaborative efforts within urban mobility. The high confidence score suggests that the data relevant to Collaboration is reliable and well-supported.
- **Governance**: With 3,125 instances and a cumulative confidence score of 2,325.416, the Governance domain is well-represented in MaaS data as it likely

contains information about the governance structures and regulatory aspects of MaaS systems.

- **Innovation**: Innovation-related data is abundant in the dataset, with 4,159 instances and a cumulative confidence score of 3,251.157. This suggests that MaaS plays a significant role in fostering innovation within urban transportation systems. The high confidence score indicates a strong foundation for research and decision-making in this domain.
- **Resource Management**: The Resource Management domain comprises 3,983 instances with a cumulative confidence score of 2,967.703. This indicates that MaaS data contains important perceptions of the efficient utilization of resources, such as transportation assets, infrastructure, and logistics. Effective resource management is critical for sustainable urban mobility.
- **Sustainability**: Sustainability-related data is represented by 2,845 instances and a cumulative confidence score of 2,060.022. The keyword within this domain includes information on environmental impacts, energy efficiency, and emissions reduction, all essential for promoting sustainable urban transportation.

The total count of instances across all domains is 17,356, with a cumulative confidence score of 13,014.236. These results demonstrate the richness of MaaS data in addressing various facets of city planning and SDGs. Further analysis and interpretation of specific data points within each domain can provide deeper insights.

5.3 SCALING-UP AND REFINING PARAMETERS

The second stage of the study, which involves an extensive dataset of 200 MaaS companies, represents a pivotal expansion in this research. This phase is instrumental in deriving concrete use cases for city planning, and its importance can be attributed to several key factors.

1. **Robust Data Analysis:** A larger dataset enables more robust statistical analyses and provides a deeper understanding of trends, correlations, and variations. It allows for more confident conclusions and enhances the validity of research findings.
2. **Increased Data Diversity**: With a larger dataset, the study encompasses a more diverse range of MaaS companies, organizational structures, and data types. This diversity provides a richer source of information to identify and

develop concrete use cases that are reflective of real-world scenarios. In contrast, the first stage, involving only 50 companies, might have limited the scope and variety of identified use cases.

3. **Fine-Grained Analysis**: The second stage's transition from five to three integration levels suggests a more focused and nuanced approach to data analysis. This finer granularity allows for a deeper understanding of how different integration levels impact city planning and SDGs. It enables the study to pinpoint specific areas where MaaS data can drive actionable solutions in urban contexts.
4. **Improved Generalizability**: The use cases developed in the second stage are likely to have broader applicability and generalizability across various urban settings. A larger dataset increases the chances of identifying common patterns and best practices that can benefit a wide range of cities, making the findings more relevant and transferable.
5. **Utilizing percentages**: Percentages provide a standardized and simplified measure that combines relevance and count, making comparing data across different categories or datasets easier. It offers several advantages over relying on relevance and count of keywords in data analysis. This weighted measure gives more importance to categories where relevance and count are high, revealing nuanced insights. Also, the consistency of the 0-100% scale is clear and aids in identifying trends and patterns.
6. **Alignment with Real-World Scenarios**: By working with a larger and more diverse dataset, the study can draw insights from MaaS companies more representative of the global landscape. This means the derived use cases are more likely to align with practical, real-world scenarios that city planners and decision-makers encounter.

While assessing the relevance of MaaS data to SDGs is valuable, concrete use cases can bridge the gap between theory and practice. The second stage will attempt to derive use cases to provide specific and actionable scenarios.

5.4 MAAS DATA AND CITY PLANNING -STAGE 02

At the culmination of the pre-processing phase of the second stage, a total of 9164 keywords were extracted, and through the implementation of curation techniques, which included the removal of duplicated entries and the summation of their respective values, this number was subsequently reduced to 4933 entries that were identified and sorted through a filtering process before being evaluated by the classifier. Ultimately, upon the conclusion of this process, a total of 1245 records were registered in the database, thereby signifying the efficacy of this multifaceted approach in parsing and organizing voluminous data sets.

A systematic process is initiated to establish a comprehensive linkage between the outputs of MaaS data and the domains of city planning, commencing with the training of data through the utilization of the ecosystem presented in section 4.3. This approach entails the classification and organization of data, as explained in section 4.6. The method (Topic modeling) employed in this process extracts the features of keywords within the text and defines their nature. The findings presented in section 4.5 which identifies five SDG domains: sustainability, resource management, governance, innovation, and collaboration. Depending on contextual usage, NLP topic modeling establishes a relativity percentage for each word. With the integration of this approach, the linkage between the MaaS data outputs and the various domains of city planning is established.

As an illustration of the process, a brief analysis of the MaaS company of Beat reveals that the following keywords have been on the top of prominently featured in their business and services: e-scooters, shared mobility, on-demand transportation, and urban transportation. By the established relevance percentages, the corresponding domains that are estimated to be most pertinent are as follows: Innovation (60%), Resource Management (50%), Collaboration (60%), Governance (50%), and Sustainability (50%). Through this meticulous process, the intricate relationship between the MaaS data outputs and the various domains of city planning is adeptly established, thereby providing a profound understanding of how these domains intersect and inform one another.

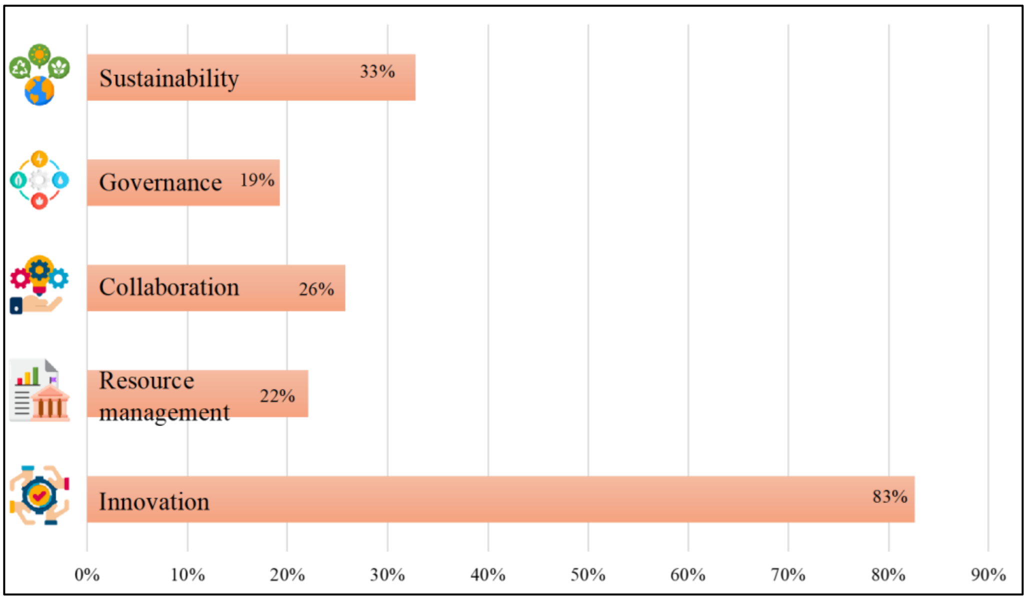

Fig. 22. Percentage of the Key Domains in MaaS Data. Source: The Author.

The ratings show the relevance of MaaS data in the innovation, sustainability, resource management, collaboration, and governance domains, providing some clarity relevant to city planning. Innovation and sustainability have the highest ratings, indicating that these aspects hold considerable importance for MaaS businesses. However, a more nuanced picture emerges when considering average ratings. Innovation, with an average rating of 83%, is perceived as significantly important overall, while Sustainability lags with an average rating of 33%. This suggests that while innovation is highly prioritized, sustainability might not receive the same attention.

Resource management and Collaboration receive lower ratings, indicating that they may not be as highly prioritized by the analyzed MaaS companies. This observation aligns with the lower average ratings of 22% for resource management and 26% for collaboration.

Governance receives the lowest sum of ratings and boasts the lowest average rating at 19%, suggesting that it is perceived as the least important category. This indicates that governance-related aspects might not receive adequate attention or emphasis in the MaaS industry. Overall, this analysis highlights the varying degrees of importance attributed to different categories by MaaS companies.

5.5 USE CASES OF MAAS DATA IN CITY PLANNING

The number of use cases generated using topic modeling depends on the data's size and diversity and the topics' granularity. A larger data set with more diverse sources will likely yield more topics and, consequently, more potential use cases. The specific method and tools used for topic modeling can influence the results. However, the primary objective of this section is to showcase the number of use cases that can be derived from the analyzed sample and examine them to discern the patterns essential for assessing MaaS data capabilities in city planning. The list of the use cases is presented in Appendix G, and Fig. 23 displays the distribution of the use cases over the SDGs domains.

1. **Collaboration (28 use cases)**:

Urban planning often involves a multitude of stakeholders, including government agencies, private companies, communities, and more. This complexity leads to numerous collaborative scenarios, resulting in a high number of use cases.

2. **Innovation (17 use cases)**:

The urban planning domain constantly evolves with technological innovations and solutions. This dynamism generates numerous use cases for adopting emerging technologies and innovative practices.

3. **Resource Management (16 use cases)**:

Resource management in urban planning encompasses a range of aspects, such as energy, waste, water, and material sourcing. Each of these aspects can generate multiple use cases. However, compared to collaboration, resource management may involve fewer actors, leading to a lower count of use cases.

4. **Sustainability (12 use cases)**:

Sustainability, while crucial, often represents a more specific set of practices and initiatives within urban planning. This specialization can lead to a moderate number of use cases compared to broader domains like collaboration.

5. **Governance (11 use cases)**:

Governance primarily deals with the policy and regulatory aspects of urban planning. While essential, these aspects may generate a limited number of use cases compared to more operationally oriented domains like resource management or collaboration.

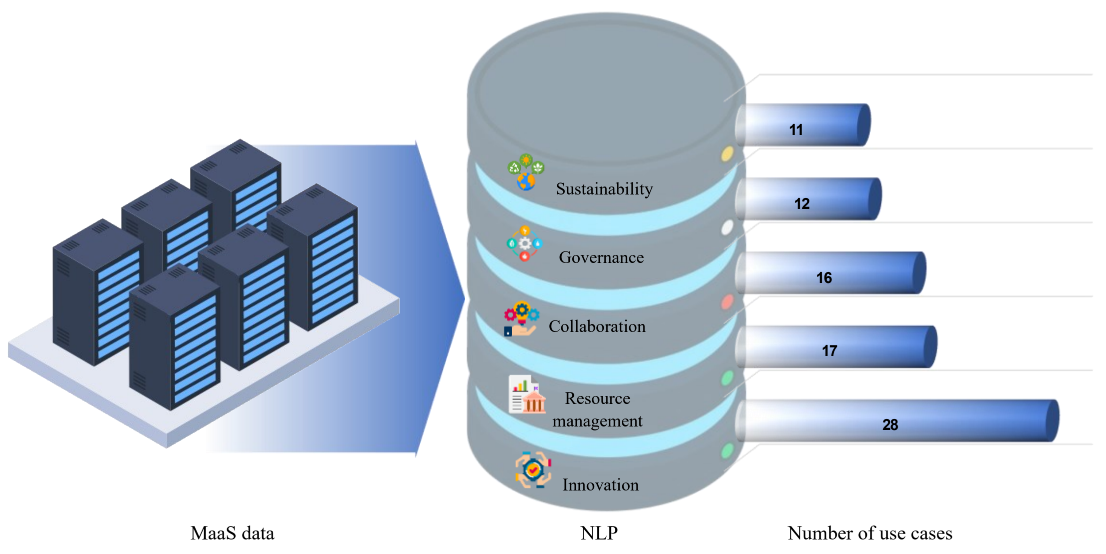

Fig. 23. Use Case Distribution Based on MaaS Data with NLP. Source: The Author.

The proliferation of MaaS systems has inundated city planners with an unprecedented volume of data, often surpassing the capacities of traditional planning tools. Integrating NLP techniques into city planning processes offers a transformative solution. NLP enables the efficient analysis of MaaS data, empowering planners to distill meaningful insights from the deluge of information. With NLP, planners gain enhanced clarity regarding mobility patterns, user behaviors, and service efficacy -in this research, alignment with SDGs- thereby facilitating more informed decision-making. Crucially, NLP helps identify gaps in transportation infrastructure and service provision, pinpointing areas for targeted interventions and improvements. By harnessing NLP to analyze MaaS data, city planners can chart a clearer course toward urban development, aligning with sustainability objectives and meeting the diverse needs of their communities.

These use cases assist city planners by offering practical insights and guidelines across various dimensions of urban development based on the MaaS system in use. Understanding collaboration scenarios enables planners to identify key stakeholders and foster partnerships for effective project implementation. Insights into innovation facilitate the integration of emerging technologies and novel practices, enhancing efficiency and sustainability in urban planning processes. Resource management use cases help optimize resource allocation, prioritize investments, and implement sustainable practices to minimize waste and environmental impact. Moreover, sustainability-focused examples provide strategies for integrating environmentally friendly practices into urban development projects, promoting resilience and long-term sustainability. Finally, governance use cases offer insights into policy frameworks and regulatory mechanisms, aiding planners in developing effective governance structures and policies to address urban challenges and ensure accountability. These use cases empower city planners to make informed decisions, foster collaboration, embrace innovation, and promote sustainable urban development.

The optimization of the MaaS system meant in this study to extract meaningful insights for more oriented usages of MaaS data, clarify the content and the type of produced data, and therefore help to opt for the right actions to take for a more sustainable and efficient urban system. Mainly, the NLP approaches in this research aim to enhance efficiency, enable better resource allocation, and support sustainability goals.

This chapter has uncovered the outcomes and findings stemming from the analysis of MaaS data using NLP techniques. These findings are the product of extensive data processing, modeling, and interpretation, shedding light on the intricate relationships between MaaS data, urban planning, and SDGs. The subsequent chapter on the discussion of the results is poised to review these results within the context of the theoretical framework crafted in the Literature Review chapter. This theoretical framework provides the support upon which the findings will be compared, contrasted, and contextualized. In the following chapter, empirical results will be linked with established theories, concepts, and prior research to extract deeper meanings, identify patterns, and draw insightful conclusions. The ambition is to contribute to the wider understanding of urban planning.

Chapter 6: Discussion

This chapter presents and compares the study results with existing literature, emphasizing their relevance in urban planning and MaaS. Section 6.1 examines the alignment of research results with the initial objectives and highlights the approach employed across various stages by reaffirming the research objectives. This is followed by section 6.2, which analyzes and interprets the relevance of key concepts of city planning and their relevance to MaaS. Each concept is interpreted, providing perceptions of their significance and application. Section 6.3 assesses the research findings in the context of approaches previously introduced in the literature chapter. Then, section 6.4 analyzes and interprets key features of MaaS organizations, providing insights into the evolving nature of the sector, the diversity in integration, and mobility offerings.

The purpose of Section 6.5 is to clarify the distinctions between urban mobility data and MaaS data, providing definitions and highlighting their sources, scopes, and primary objectives. It aims to emphasize the specific role of MaaS data in supporting integrated and user-centric transportation services, contributing to more informed city planning and sustainable urban mobility practices.

6.1 RESTATEMENT OF RESEARCH OBJECTIVES

This section explores the way the results and the findings align with the initial research objectives and discusses the research's approach to addressing these objectives throughout various stages.

The key objectives of this research on MaaS data, highlighted in section 1.3, are to (1) investigate and identify the essential characteristics of MaaS organizations to enhance their integration into the city system, (2) conduct an in-depth exploration of the MaaS ecosystem, including its data types, while providing clear definitions, and (3) identify and integrate MaaS data in a manner that effectively supports and advances city planning with a comprehensive grasp of the contextual, eco-systemic, and business model definitions related to MaaS. This research attempts to progress the frontiers of scholarship in this field by shedding light on the latest developments and advancements in the field of NLP, generating insights that can enhance the usability of MaaS data for city planning.

The research handled the objectives through the following chapters:

1. Literature Review: In this chapter, the research reviewed the existing literature on MaaS and related fields, identified gaps in the literature, and presented a theoretical framework that provides the support upon which the findings will be compared, contrasted, and contextualized. The chapter also presented other methods related to the research objectives and comparable to NLP, delineated in alignment with the research objectives and their relevance and applicability.

2. Research Design: In this chapter, the research design was presented, including the research questions, data collection methods, data analysis techniques, and the conceptual framework to meet the research objectives.

3. Results: In this chapter, the research presented the empirical results of the study, including the analysis of MaaS data and the identification of its trending applicable domains. The analysis was based on the sum of confidence and relevance counts, with results from the first and second stages of the research and an interpretation considering these criteria. The goal was to offer further insights into the results and their potential implications.

In this chapter, the research restated the objectives in a way that addresses the questions of the study and reminds readers of the focus. The chapter also summarizes the key findings of the study and presents them in a clear and concise manner.

Overall, the research design and mode chapters provided a comprehensive analysis of the MaaS data, identified its trending applicable domains, and compared the research findings with those of similar tools. The literature review chapter provided a theoretical framework that contextualized the findings, while the results chapter summarized the key findings of the study.

6.2 INTERPRETATION OF RESULTS

Based on the count of relevance, the concept of innovation has the highest relevance score (4159), followed by resource management (3983) and collaboration (3244), which are also very relevant to MaaS data. Next comes the governance with (3125). Sustainability is reported to be the least frequent on the list, with (a 2845) count.

Based on the sum of confidence, the first term remains innovation with (3251,157), followed by resource management as well with (2967,703). After that, collaboration and governance followed (2409,938) and (2325,416) respectively. In the end, sustainability comes last with a sum of (2060,022).

The relevance of each concept to MaaS is interpreted as follows:

6.2.1 Innovation

Innovation is highly relevant to MaaS since it relies on the development and implementation of new technologies and business models to provide users with convenient, accessible, and sustainable transportation options. As MaaS involves the integration of various modes of transportation into a single service platform, it requires the development of innovative technologies and systems to manage and coordinate these different modes of transportation. In addition, MaaS involves the use of new technologies, such as sensors, data analytics, and AI, to improve the efficiency and effectiveness of transportation services. As a result, innovation is a key driver of the MaaS industry, and many MaaS providers are constantly looking for new ways to innovate and improve their services. And that explains the highly frequently used innovative concepts in the MaaS data.

6.2.2 Resource management

In the context of MaaS, resource management refers to the effective use of transportation infrastructure and vehicles to provide efficient and convenient mobility services to users. It involves managing the availability and allocation of mobility resources, including buses, trains, cars, bikes, and other forms of transportation that are available on the platform. This can also vary depending on the location and the specific MaaS provider. Resource management ensures that these resources are used in the most efficient and effective manner possible. By managing these resources effectively, MaaS providers can help to reduce congestion and improve the overall transportation experience for users.

Resource management is important for MaaS. It entails making sure that the various transportation resources offered by the MaaS platform are deployed effectively and efficiently. This can help to reduce congestion, minimize the environmental impact of transportation, and improve the overall user experience. For example, by using algorithms to optimize routing and scheduling, a MaaS provider can help to reduce the number of empty vehicles on the road and reduce the amount of time users spend waiting for a ride. Additionally, by using data and analytics, a MaaS provider can monitor and adjust the supply of transportation resources in real time to meet changing demand. This can help to ensure that users have access to the transportation services they need and when and where they need them.

6.2.3 Collaboration

The collaboration for MaaS involves the coordination and cooperation among different transportation providers and stakeholders to support the development and operation of the MaaS platform. It includes public transit agencies, ride-hailing companies, car-sharing services, bike-sharing programs, and other transportation providers. The collaboration in this context involves the sharing of data and information among these different stakeholders, as well as the development of common standards and protocols for data sharing and interoperability. Collaboration for MaaS also requires the coordination of planning and operations among different transportation providers to ensure that the MaaS platform provides a seamless and integrated user experience.

Collaboration is crucial for MaaS because it supports the development of a sustainable and efficient transportation system that meets the needs of users. Collaboration is also important for MaaS because it can help ensure that the transportation services available through the MaaS platform are sustainable and efficient, reducing congestion and minimizing the environmental impact of transportation.

6.2.4 Governance

Governance for MaaS involves the development and implementation of policies and regulations that affect the operation and use of the MaaS platform. This includes decisions about the types of transportation services that are available through MaaS, the areas in which MaaS services are offered, and the rules and regulations that apply to the use of these services. Governance for MaaS also involves the development of standards and protocols for data sharing and interoperability among different MaaS providers and stakeholders, as well as mechanisms for monitoring and enforcing compliance with these policies and regulations. The specific details of MaaS' governance vary depending on the local context and the goals and objectives of the MaaS provider.

The governance of MaaS is significant for urban planning because it helps to ensure that the MaaS platform can support the broader goals and objectives of the city or region. For example, by establishing policies and regulations that encourage the use of sustainable and shared modes of transportation, the governance of MaaS can support urban planning efforts to reduce congestion, improve air quality, and promote social equity. Additionally, by establishing standards and protocols for data sharing and interoperability among different MaaS providers and stakeholders, the governance of MaaS can support urban planning efforts to create a seamless and integrated transportation system that is easy to use and navigate. By providing a framework for decision-making and coordination among different transportation providers and stakeholders, the governance of MaaS can also support urban planning efforts to ensure that the transportation system is responsive to the needs and preferences of users.

6.2.5 Sustainability

Despite ranking last in the list, sustainability is highly relevant to MaaS as it involves the development and operation of a transportation system that is environmentally friendly and socially equitable. Also, by providing a range of sustainable and shared transportation options, MaaS can help reduce the number of private cars on the road and decrease the environmental impact of transportation. For example, by promoting the use of public transit, car sharing, and bike sharing, MaaS can help reduce the amount of greenhouse gas emissions and other pollutants associated with transportation. Additionally, by making sustainable transportation options more convenient and affordable, MaaS can help to improve access to opportunities and reduce transportation-related barriers for underserved communities. By supporting the development of a sustainable transportation system, MaaS can play an important role in efforts to create livable and equitable cities.

Since the focus of most MaaS enterprises has been on improving the efficiency and effectiveness of their systems rather than on environmental or social concerns, the term Sustainability is not mentioned and applied much within MaaS data. The current trends are focused mostly on technical and operational issues, such as routing and scheduling, traffic flow, and infrastructure design, rather than on sustainability. Additionally, many MaaS providers have been more focused on meeting the demands of the existing transportation system rather than on exploring new, more sustainable alternatives. However, in recent years, there has been increasing recognition of the need to integrate sustainability into mobility planning in general and decision-making.

There is growing interest in exploring the potential role of MaaS in supporting sustainable transportation.

6.3 DISCUSSION AND EVALUATION OF RELATED METHODS

In this section, approaches similar to NLP presented in section 2.4 will be analyzed, along with their alignment with the research goals. Furthermore, the practical implications of their application in real-world urban planning scenarios will be considered. Through this evaluation, an effort is made to support the robustness and credibility of this research method amongst the conceptual framework, ensuring that the standards of scientific examination are met.

The first considered approach is Google N-Gram. This approach has the potential to supplement this study by providing historical and linguistic context, identifying trends in mobility-related language, and helping with the assessment of how the language in the dataset compares to broader linguistic trends. It represents an ideal tool for certain aspects of the research, particularly when examining long-term language shifts and trends in mobility discourse.

6.3.1 Google N-Gram and MaaS data

The present study has shed light on the importance of matching MaaS data with specific city planning practices, which have varying degrees of relevance to the urban environment. To determine the extent of success in achieving this task, the Google N-gram Viewer is used to chart the frequencies of search strings. The use of N-grams, which are analytical tools that calculate the likelihood of specific words or phrases appearing together in each text or speech, has become increasingly common in NLP and other fields as a means of predicting the next word or phrase in each sequence.

Thus, the application of N-grams in the present study can offer critical viewpoints into the interrelatedness between different factors and their impact on the overall success of MaaS integration with city planning practices. By analyzing the frequency and co-occurrence of specific keywords and phrases, the study can provide a deeper understanding of the complex relationships between different variables and identify potential areas for improvement in terms of procedure and implementation.

N-gram is a contiguous sequence of n items from a given sample of text or speech, extensively used in text mining and natural language processing tasks. When testing the frequency of the domains. Google Books N-gram Viewer displays a graph showing how those phrases have occurred in a corpus of books. Generally, the expected exports from n-gram text mining depend on the specific goals and objectives of the text mining project. The outputs from n-gram text mining include:

- A list of the most common n-grams in the text, along with the frequency of each n-gram
- Visualizations of the distribution of n-grams in the text, such as bar charts or word clouds
- Statistical analyses of the n-grams, such as measures of central tendency (e.g., mean, median) and variability (e.g., standard deviation)
- Models that can be used to predict the likelihood of certain n-grams appearing in new text.
- Insights and patterns are discovered through the analysis of n-grams, such as common themes or trends in the text.

The outputs derived from n-gram text mining have the potential to yield value in terms of understanding the structure and substance of the textual material under examination, see Fig. 24.

Innovation is a concept that reigns supreme in both the present research approach and the N-gram, capturing the attention of scholars and practitioners alike. Following closely behind is **governance**, which is ubiquitous in various political, international, and national contexts. However, in the approach of this study, governance is limited to the realm of urban planning and city governance, explaining its placement in fourth place.

Collaboration is the third most frequently occurring concept in Google Books and in this research, highlighting its significance as a crucial aspect of innovation and governance. Sustainability, while considered important, surprisingly finds itself in the penultimate position in the city planning domain despite the concerted efforts of governments worldwide to promote its importance.

Finally, **resource management** secures the last position with less than 0.00050% frequency, despite its fundamental role in city planning. The infrequent occurrence might stem from the fact that the term could be synonymous with a single word, resulting in fewer occurrences as a string. Nonetheless, its placement as the second most important concept in city planning underscores its importance in managing and optimizing the use of available resources for sustainable development.

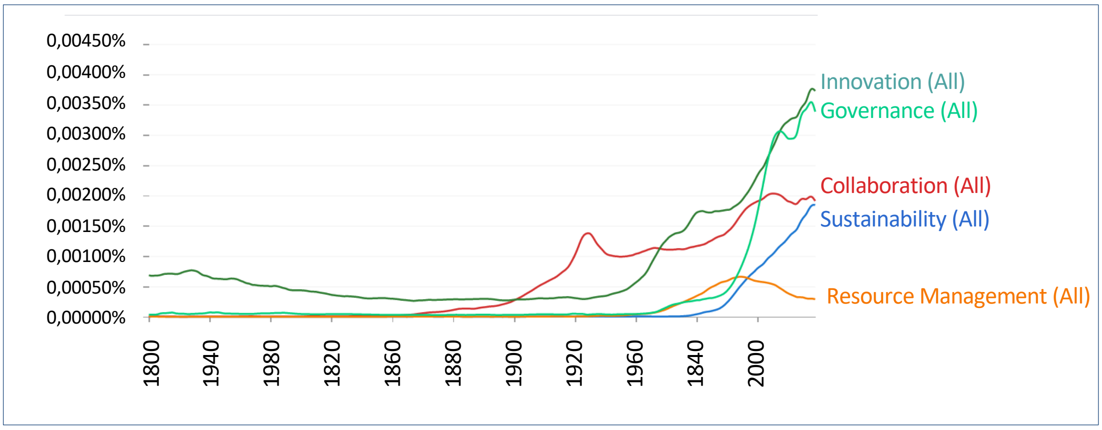

Fig. 24. The Sequence of the City Planning Domains on N-gram. Source: The Author.

However, the differing frequency of these concepts in the MaaS data results compared to the n-gram analysis suggests that the specific priorities and emphasis within the MaaS industry and urban planning context vary. For example, sustainability, despite being a global focus, still has a different level of prominence in the MaaS data study, reflecting the unique challenges and goals of the MaaS sector.

In summary, while there are commonalities in the importance of certain concepts like innovation and governance, the specific frequencies and nuances of these concepts in the MaaS data study would require a separate analysis to draw conclusive insights about their relevance and prioritization within the MaaS industry and urban planning.

The other approaches to categorize the usability of data have been identified in section 2.4 as the following: Cloud Natural Language, IBM Watson Natural Language, Graph databases and triple stores, and TimeML. In this section, the evaluation will be made based on the results and the findings from Chapter 5:.

6.3.2 Cloud Natural Language

While NLP offers expanded possibilities for city planning research, it also presents challenges such as skill acquisition, data quality, privacy concerns, and ethical considerations. Cloud Natural Language services, on the other hand, provide convenience and reliability but require adapting research goals to their service limitations. The choice between the two hinged on the research objectives. The following are the main advantages of NLP over Cloud Natural Language.

- **Data Volume**: NLP is preferable when handling large datasets that surpass the limitations of Cloud Natural Language services. However, it requires more computational resources and technical expertise.
- **Language Support and Features:** NLP offers broader language support and additional features like speech recognition, machine translation, and text summarization. These capabilities are not uniformly available or accurate in Cloud Natural Language services, depending on the language or domain.
- **Flexibility and Control**: NLP provides greater flexibility and control over the design and implementation of the systems. Researchers can choose from various frameworks, libraries, models, and algorithms, enabling customization to specific research needs.

The choice between NLP and cloud natural language services for city planning research depends on a range of factors. While NLP offers expanded possibilities for research, it comes with challenges. Ultimately, the decision should align with research objectives and the willingness to navigate complexities while striking a balance between simplicity and customization.

6.3.3 IBM Watson Natural Language

The research findings suggest that NLP can provide comprehensive and adaptable solutions for handling complex language nuances and domain-specific challenges. Compared to cloud-based services like IBM Watson Natural Language, factors like flexibility, language support, and the ability to customize models make NLP a preferred choice for researchers working with diverse textual data and aiming for precise and contextually relevant results. Here are the NLP's key advantages:

- **Enhanced Language Processing:** NLP can better handle complex or ambiguous sentences, idioms, and metaphors due to its advanced algorithms and models. It excels in understanding the intricacies of human language, making it suitable for analyzing diverse and nuanced textual data.
- **Customization:** NLP offers the flexibility to tailor language models and processing pipelines to specific research needs. Researchers can fine-tune models, incorporate domain-specific terminology, and adapt the system to unique language challenges, improving accuracy and relevance for their particular field.

- **Broad language and feature support:** NLP supports a wider range of languages and features, including speech recognition, machine translation, text summarization, question answering, and more. This versatility allowed this research to handle diverse language datasets from international MaaS companies with different languages and process them with a rich set of linguistic capabilities.
- **Data availability:** Unlike cloud-based solutions that rely on pre-trained models and struggle with languages or dialects with limited data availability, NLP can leverage various data sources and techniques to improve language understanding. This Research could incorporate additional training data in the second stage and enhance the model´s performance.
- **Latest Advances:** NLP enables researchers to harness the latest advancements in natural language processing, including deep learning, transformer models, attention mechanisms, and more. Staying at the forefront of technology can lead to more accurate and innovative research outcomes.

In addition to these factors, it is crucial to consider the specific research context and objectives. Ultimately, the decision should be driven by the unique demands and objectives of the research project.

6.3.4 Graph databases and triple stores

The advantages of NLP in city planning studies compared to graph databases and triple stores include:

- **Language Understanding**: NLP excels at understanding and processing natural language, allowing it to capture nuances, subtleties, and context in textual data. This is crucial in city planning studies, where documents and reports often contain complex language and varied interpretations.
- **Contextual Analysis**: NLP can analyze text in its contextual framework, considering the pragmatics, discourse, and rhetoric used in language. This contextual analysis is important to comprehend the broader meaning of textual data, which is essential in urban planning studies.
- **Handling Uncertainty**: NLP models can handle uncertainty, vagueness, and inconsistency in natural language data to some extent. They use probabilistic

approaches and can provide more flexibility in dealing with ambiguous information.

- **Automated Processing**: NLP systems can automate many aspects of text analysis, reducing the need for extensive manual effort in creating data schemas and queries. This automation streamlines the process and allows researchers to focus on analysis rather than data preparation.

Overall, NLP offers a more advanced and adaptable approach to processing textual data in city planning studies, considering the complexities of language, and reducing manual labor compared to graph databases and triple stores.

6.3.5 TimeML

The advantages of NLP in city planning studies compared to TimeML include:

- **Handling Complex Temporal Expressions**: NLP models are capable of handling a wide range of temporal expressions, including those that are implicit, vague, or relative. The findings suggest that this ability is crucial where time-related information can be intricate and multifaceted.
- **Temporal Reasoning and Inference**: NLP can perform sophisticated temporal reasoning and inference tasks, such as determining causality, establishing chronological order, and estimating durations. This capability enables a deeper understanding of time-related aspects in MaaS data.
- **Coverage of Temporal Phenomena**: NLP models generally offer broader coverage of temporal phenomena, encompassing various aspects of time in textual data. This extensive coverage ensures that relevant temporal information was overlooked during the analysis of this study.
- **Inter-Annotator Agreement**: NLP systems, when properly trained and validated, can achieve higher inter-annotator agreement compared to manual annotation with TimeML. This results in a more consistent and reliable temporal analysis.

In summary, NLP provides a more versatile and comprehensive approach to handling temporal aspects in city planning studies, addressing challenges related to complex expressions and reasoning and achieving better coverage and agreement on temporal phenomena compared to TimeML.

6.4 MAAS ORGANIZATIONS FEATURES INTERPRETATION

This research shed light on the applicability of MaaS data in city planning and how future mobility modes can provide more improvements to additional sectors other than mobility. Drawing on the findings of this study, several interpretations can be inferred:

- The **Year of Creation** for the companies varies widely, with some dating back as far as 2007 and others being as recent as 2021, indicating that the MaaS sector is constantly evolving and growing.
- The Level of Integration also varies, with some companies being classified as low, some as medium, and others as high. This suggests that the mobility sector is highly diverse, with different companies and platforms offering different levels of integration and connectivity.
- The Number of Mobility Modes offered by each company also varies widely, with some companies offering only three modes while others offer as many as nine. This highlights the diversity and complexity of the MaaS domain, with different companies offering different types of mobility solutions.
- Some companies have achieved significant success and growth, such as Didi Chuxing, which was founded in 2012 and now offers seven mobility modes. This suggests that there is significant potential for growth and expansion within the MaaS sector.
- Many of the companies listed are focused on providing sustainable mobility solutions, such as electric scooters or car-sharing platforms. This indicates that sustainability is becoming an increasingly important factor within the MaaS realm.
- Most of the companies listed are focused on providing mobility solutions in urban areas, indicating that urban mobility is a key focus for the industry.
- The MaaS sector is highly competitive, with many companies offering similar types of services and competing for market share.
- The COVID-19 pandemic has had a significant impact on the MaaS sector, with many companies experiencing reduced demand for their services because of lockdowns and restrictions on travel. This highlights the need for the MaaS models to be flexible and adaptable in response to changing circumstances.

However, cities and regions that adopted advanced mobility systems were more resilient (Hatcha, 2022).

6.5 COMPARING MAAS DATA WITH URBAN MOBILITY DATA FOR INFORMED CITY PLANNING

Urban mobility data and MaaS data are related but differ in their scope and purpose:

Definition

Urban mobility data is a broad term that encompasses all types of data related to transportation and movement within urban areas. MaaS data specifically refers to data generated and collected within its framework, which is a concept aimed at providing integrated and seamless transportation services to users.

Sources

Urban mobility data can include data from various sources, such as traffic sensors, public transportation agencies, GPS data from vehicles, ride-sharing services, parking data, and more. However, MaaS data is often collected from various MaaS providers, which can include ride-sharing companies, public transit agencies, bike-sharing services, and more. It also includes data from MaaS apps used by consumers.

Scope

Urban mobility data covers a wide range of transportation aspects, including traffic flow, congestion, public transit schedules, road conditions, parking availability, and more. MaaS data focuses on the user experience and the integration of various transportation modes into a single service. It includes information on trip planning, booking, payment, and user preferences.

Purpose

The primary purpose of urban mobility data is to monitor and manage transportation systems, improve traffic flow, enhance public transportation services, and address urban mobility challenges.

The primary purpose of MaaS data is to support the delivery of integrated and convenient transportation options to users. It aims to improve the efficiency of transportation services, reduce the reliance on private car ownership, and promote sustainable urban mobility.

While urban mobility data is a broader category encompassing various aspects of urban transportation, MaaS data is more specific and relates to the implementation of integrated mobility services that offer users a seamless travel experience. MaaS data plays a crucial role in achieving the goals of reducing congestion, promoting sustainability, and enhancing urban mobility.

Chapter 7: Conclusions

The primary purpose of the study at hand is to determine the various aspects and degree to which MaaS data can be effectively employed in the domain of city planning. The answer to this question required a broad investigation of MaaS and its contextual, eco-systemic, and data definitions to identify what can be utilized in a way that aligns with city development goals. Ultimately, the aim is to identify and integrate MaaS data in a manner that effectively supports and advances the sustainability of cities. By diving deep into this topic, it becomes evident that the identification and classification of the various sorts of MaaS data represent an asset for further exploitation.

This chapter starts by assessing the formulated hypotheses in section 7.1 through an analysis of the results and a detailed discussion; these hypotheses are either confirmed or refuted, accompanied by an explanation and a summary of the main findings in section 7.2. Section 7.3 presents some of the study results and their implications. The limitations of the study are presented in section 7.4. Finally, section 7.5 addresses general recommendations related to the research subject, retained lessons, and potential development.

7.1 EVALUATION OF THE RESEARCH HYPOTHESIS

This section involves subjecting the proposed ideas to an examination, employing various research methods and data analysis techniques to determine their validity. In this study, three main hypotheses were established:

7.1.1 Hypothesis 1

The first tests related to MaaS organizations integration derive three hypotheses, as follows:

Hypothesis 1.1: Comparative Analysis of MaaS Integration Levels (Private vs. Public)

In this test, the aim is to determine whether there is a significant difference in the mean integration levels between private and public MaaS companies. As motioned in section 1.6, the null hypothesis (H_0) stated that there is no significant difference, while the alternative hypothesis (H_1) posited that a significant difference exists between these two groups.

The t-test results, both when assuming equal variances and when not assuming equal variances, indicate that there is **no statistically significant** difference in the mean integration levels between private and public MaaS companies. Thus, the data collected does not provide strong evidence to suggest a significant difference in integration levels based on the company's public or private status.

Hypothesis 1.2: Relationship Between Years Since Creation and Integration Level

This hypothesis sought to assess whether the number of years since the creation of a MaaS company has any relationship with its integration level. As stated in section 1.6, the null hypothesis (H_0) recognized that there is no significant association between these two variables, while the alternative hypothesis (H_1) proposed that there is indeed a significant relationship between the number of years since creation and integration level.

The chi-square test reveals that there is a **statistically significant association** between the number of years since the creation of MaaS companies and their integration levels. This suggests that, according to the data, there is a meaningful relationship between the age of a MaaS company and its level of integration, indicating that older companies tend to have higher integration levels compared to newer ones.

Hypothesis 1.3: Relationship Between Integration Level and Number of Mobility Modes

For this hypothesis, the relationship between the integration level of MaaS companies and the number of mobility modes they offer is investigated. In this research hypothesis, section 1.6, the null hypothesis (H_0) asserted that there is no relationship between these variables, whereas the alternative hypothesis (H_1) suggested that a relationship does exist, implying that integration level and the number of mobility modes are dependent variables.

The chi-square test results support the conclusion that there is a **statistically significant relationship** between the integration level of MaaS companies and the number of mobility modes they provide. This underscores the importance of the variety of mobility modes offered by MaaS companies in influencing their continuous integration in the urban system based on the dataset analyzed.

7.1.2 Hypothesis 2

Based on the hypothesis that MaaS data can be leveraged to support SDGs and enhance the sustainability of cities, the study sought to explore the potential use cases and insights that could be derived from this data. The results of the analysis indeed demonstrated that MaaS data can be effectively processed to generate enlightening observations and even city planning use cases that align with SDGs and can contribute to the overall sustainability of cities. Furthermore, the study highlighted that the generation of these use cases is contingent upon the quality, quantity, and diversity of the MaaS data available. In essence, the findings emphasize the substantial role that MaaS data can play in advancing the objectives of urban sustainability and informed decision-making systems for cities.

7.1.3 Hypothesis 3

The results of the study support the hypothesis that cities with more advanced mobility systems exhibit greater resilience during pandemics. Through an analysis of various cities and their mobility infrastructures, it was observed that those with well-established MaaS and advanced mobility systems demonstrated more effective responses to the pandemic. These cities experienced fewer disruptions in their mobility services, including public transportation, and exhibited better control over the spread of the virus. The ability to adapt and optimize mobility resources, such as ride-sharing and real-time data analysis, played a pivotal role in mitigating the impact of the pandemic on urban mobility patterns. This suggests that investments in advanced mobility technologies can indeed contribute to increased resilience in urban settings during times of crisis.

7.2 SUMMARY OF THE MAIN FINDINGS

The findings of the research indicate that NLP can be a valuable tool in facilitating the categorization and labeling of the vast and multifaceted data generated by the field of MaaS, thereby enabling a more precise definition of its utilization and exploitation. Despite the enormity and intricacy of the data, NLP is instrumental in filtering and organizing it into distinct groups, allowing for a more detailed analysis and comprehension of its constituents and components. By leveraging NLP, interested parties develop more concrete assumptions regarding the data, establish clear indicators, and avoid the tendency to employ broad approaches and expectations that may not accurately reflect the intricacies of the information at hand. Therefore, NLP serves as a critical asset in facilitating a more in-depth and precise understanding of the MaaS data, thereby enabling more informed decisions and insights.

The present study highlights the advantages of utilizing NLP in the context of urban data sources, demonstrating its efficacy in broadening the scope of studies while simultaneously reducing research expenses and time. Nonetheless, it is crucial to avoid posing blurry and vague research questions, as such ambiguity can undermine the effectiveness of NLP techniques. In addition, selecting appropriate, accessible, and representative data sources, in conjunction with adopting the appropriate NLP approaches, is of paramount importance for researchers in the urban domain seeking to benefit from the implementation of NLP techniques. By prioritizing these considerations, urban researchers can reap the full benefits of NLP in terms of increased data usability, enhanced study scope, and efficiency gains while simultaneously avoiding the pitfalls that can impede the effectiveness of this technology. Ultimately, the judicious utilization of NLP in urban research endeavors can facilitate more informed and insightful decision-making, enabling urban planners to address the complex challenges facing cities today with greater accuracy and efficacy.

The analysis of MaaS data reveals a wealth of information concerning the transportation options utilized by commuters, the specific routes taken, and the times at which these services are employed. By contrast, urban mobility data encompasses a broader range of information, encompassing the movement of both people and goods within the confines of a given city. This extensive dataset includes information related to all modes of transportation, spanning public transportation, personal vehicles, freight transport, and non-motorized means of transit, such as walking and biking. Additionally, it incorporates data pertaining to traffic flow, congestion levels, and other critical factors that influence the movement of people and goods throughout an urban landscape.

The distinction between these two datasets is critical, as they provide complementary perspectives that are essential for a comprehensive understanding of urban transportation systems. While MaaS data focuses on the utilization of specific transportation services, urban mobility data illuminates the broader context within which these services operate, shedding light on the intricate dynamics that shape the movement of people and goods within urban environments. As such, the separation of these two datasets is crucial for effective urban planning and policymaking, as it enables decision-makers to obtain a more nuanced and multifaceted understanding of the complex transportation challenges facing cities today.

The design of MaaS platforms is a critical component of sustainable and socially responsible urban transportation systems. Given the far-reaching implications of MaaS design, it is essential that these systems be regulated at a high level by governmental bodies, particularly with regard to the advanced levels of integration required to achieve optimal efficiency and effectiveness. By prioritizing sustainability and other societal goals, government officials can ensure that MaaS platforms are developed in a manner that serves the best interests of the wider community.

Despite the importance of government involvement in MaaS design, it is also clear that private-sector cooperation is essential for the effective operation of these platforms. Indeed, evidence supports the notion that both local and private initiatives are required to generate the dynamic and adaptable MaaS ecosystem necessary to address the complex challenges of urban transportation. By working in partnership with the private sector, government officials can leverage the strengths of each sector to create an integrated and robust MaaS platform that is capable of meeting the evolving needs of urban populations.

The COVID-19 pandemic has had a major impact on the MaaS industry. As a result of the pandemic, many people have been reluctant to use public transportation, leading to a decrease in the demand for MaaS services. In addition, many MaaS providers have had to temporarily suspend or reduce their services due to the pandemic, which has further impacted the industry. In some cases, MaaS providers have had to adapt their services to meet the needs of their users during the pandemic, such as by implementing measures to ensure the cleanliness and safety of their vehicles. Generally, the COVID-19 pandemic has posed significant challenges to the MaaS industry but has also created opportunities for innovation and adaptation.

This research suggests that cities with more advanced mobility systems have less mobility of people in pandemic times, while it does not interfere much with contact between individuals. While sophisticated and advanced mobility systems are meant to have more attractiveness and positively affect the traveler's satisfaction, the results suggest that no clear and discernible impacts during the pandemic were observed. On the contrary, more multimodal trips, sharing options, and smarter mobility systems were associated with less mobility of people. Yet, it did not interfere with the contact between people during the different stages of COVID-19 in Germany.

Using technology and data to increase the effectiveness, sustainability, and accessibility of mobility systems refers to smart mobility. It can potentially reduce and slow down the spread of the virus. It can contribute to the efforts to contain the pandemic. For instance, smart mobility solutions can help restrict physical contact and allow authorities to promptly recognize and respond to possible epidemics. These options include contactless payment methods and real-time tracking of public transportation. Using shared and on-demand transportation options, like ride-hailing and bike-sharing, can also help reduce the number of PT users, significantly lowering the risk of pathogen transmission.

This study provides another viewpoint on the potential impacts of mobility advancement on people's mobility during a crisis. The substantial return to PT and ride-sharing are necessary but not satisfactory conditions. However, more efforts will be needed to enable a more hygienic shared mode environment. The shift in the behavior of urban mobility users could open new opportunities for more individualized services and options, such as MaaS, enabling many technologies to take place and play a significant role in defining the future mobility picture.

The proposed approach clarifies the discussion of such a trending topic and enables the positioning of services along the MaaS spectrum. It also deepens the understanding of why MaaS can take time to establish and can help support the development of action plans in terms of what needs to be done, depending on what type of MaaS one wants to develop.

The current study provides a helpful viewpoint that can encourage the advancement of smart systems in the realm of MaaS. It sheds light on the urgent requirement for data-driven solutions while concurrently exposing the inadequacy of the existing knowledge base to meet the needs of this burgeoning community. These findings underscore the criticality of delving further into the exploration of technological potential and knowledge in MaaS, as it is imperative to bridge the current knowledge gap through additional research endeavors. In essence, the ramifications of this study are invaluable, as they provide meaningful perspectives that can support and contribute to fostering the innovation of intelligent systems in the MaaS domain while simultaneously emphasizing the crucial need for future investigations in this field.

Through the literature part, it has been confirmed that the literature produced in the MaaS topic does not reflect its factual growth; some evidence of the multidisciplinary publications and the subtopic is technically related, with a hidden relevance, but not expressed as part of the MaaS. Hence, additional examination of the MaaS market growth, technological development, and external documentation was required to support the research on the current state of the art and delineate the rational and practical status of MaaS.

The utilization of AI tools represents an asset in pursuing effective research endeavors. In particular, the research area of MaaS and its correlation with the COVID-19 pandemic has produced a copious amount of literature, rendering it a daunting task to thoroughly review and comprehend the current state of the art, let alone identify any research gaps. In this context, AI tools can significantly enhance the preliminary reading phase by prioritizing the materials to be reviewed, thereby allowing for a more efficient and comprehensive understanding of the selected research. These tools also provide key insights that aid in conducting a more profound and reflective scan of pertinent research. However, it is important to note that the primary responsibility of reflecting, synthesizing, and determining the appropriate approach to address the research question remains with the researcher. Moreover, the knowledge garnered from prior research and ongoing work can enable the researcher to contribute more to the field.

7.3 IMPLICATIONS OF THE FINDINGS

This section encapsulates the key conclusions drawn from this study into MaaS data integration within urban planning. It starts by examining the influence of ownership status, company age, and mobility mode variety on integration levels, which can provide city planners with the knowledge to inform their strategies and decisions. Then, it presents some applications of the post-processed data out of the NLP approach within the context of this study. In the end, it presents the implications of the findings on the role MaaS can play in mitigating pandemic risks.

7.3.1 MaaS organizations integration

City planners can leverage the knowledge that ownership status (public or private) has no impact on the integration of the MaaS system. This insight allows them to make decisions based on the quality of services and integration potential rather than being influenced by organizational structures. For instance, when selecting MaaS partners for urban projects, the priority of selecting providers will be given to their alignment with city goals rather than focusing on their ownership type.

Also, understanding the positive correlation between company age and integration levels can lead to more strategic partnerships. City planners can actively seek collaborations with older, more established MaaS companies. These companies may have a deeper understanding of urban transportation dynamics and can offer more mature solutions. Such partnerships can result in more stable and effective initiatives.

The realization of the significance of mobility mode variety also provides an opportunity for city planners to shape urban mobility offerings. Planners can incentivize and encourage MaaS companies to diversify their mobility modes. For example, they can work with providers to introduce shared bikes, scooters, or electric vehicles, thereby enhancing the overall urban transportation ecosystem. This will not only offer more choices for residents but also contribute to sustainability goals.

The findings can directly inform policy development in city planning. Planners can craft policies with a better understanding of the factors that influence MaaS integration. The results also pave a solid ground for future research in data analysis and city planning, with a focus on big data and smart cities. Researchers can delve deeper into understanding why older MaaS companies tend to have higher integration levels. This exploration can uncover more insights into best practices and strategies for achieving urban mobility integration. Moreover, research can focus on the mechanisms behind the relationship between mobility mode variety and integration levels, leading to more evidence-based planning and decision-making.

7.3.2 MaaS data exploitation

In the context of the study at hand, the implications offer more insights into the practical applications and potential outcomes of the research findings. They shed light on how the knowledge and data acquired can be harnessed to drive positive change, inform strategies, and inspire innovation. In the following discussion, the key implications derived from this study will be explored, outlining their significance and relevance in addressing contemporary challenges and advancing the sustainability of future cities.

a. Complex Data Handling

Smart city systems generate and process vast amounts of data from various sources, including sensors, cameras, and connected devices. To optimize these systems, sophisticated algorithms are required to handle complex datasets efficiently (Zamponi & Barbierato, 2022). These algorithms should be capable of extracting meaningful insights, detecting patterns, and making informed decisions based on the diverse and dynamic data streams generated within a smart city environment. In this sense, this study's contribution to handling complex urban data processes lies in its ability to:

1. **Data Organization:** By clustering MaaS data types, the study helps structure the data landscape. This is crucial in managing the massive volume of data generated in smart cities, as it provides a framework for understanding and categorizing the information available.
2. **Stakeholder Definition:** Identifying stakeholders involved in MaaS data utilization clarifies who can benefit from the data and who should be involved in its management. This ensures that data is handled efficiently and that relevant parties can access and use it effectively.
3. **Usability Assessment:** Assessing how MaaS data can be used to reach SDGs goals is vital for setting clear objectives for data utilization. It aligns data collection efforts with broader sustainability and development targets.
4. **Use Case Development:** Suggesting real-life use cases based on the provided data demonstrates the practical applications of MaaS data. These use cases serve as concrete examples of how data can be leveraged to address specific urban challenges or enhance services.

In the broader context of smart cities, where a multitude of data is generated, the study contributes to a structured and purpose-driven approach to handling complex urban data. It helps ensure that data becomes a valuable asset in smart city decision-making, ultimately improving the efficiency and quality of urban services and contributing to sustainable development goals.

b. Automated smart city system

The realization of a fully automated smart city system still poses several challenges (Tarana S, 2022). Unusual events and anomalies may occur, and it is necessary to develop systems capable of detecting and mitigating these events in real-time. To address this, there is a critical need to develop systems capable of swiftly and accurately detecting and mitigating these unforeseen events in real-time. This real-time responsiveness is pivotal in ensuring the reliability, safety, and efficiency of the smart city operations (Bibri et al., 2023), as it enables immediate actions to be taken to minimize disruptions and maintain the system's functionality even in the face of unexpected occurrences. In this context, this research can make a significant contribution:

1. **Data Organization:** Clustering MaaS data types helps in organizing and structuring the information generated by various elements in the ecosystem. This organized data is easier to manage and analyze within the urban context.
2. **Stakeholder Collaboration:** Defining stakeholders and their roles in using MaaS data fosters collaboration among different parties involved in urban planning. This collaborative approach enhances data sharing and coordination.
3. **Usability Assessment:** Assessing the usability of MaaS data in reaching SDGs allows city planners to determine the practical value of this data for achieving sustainability goals. It helps in identifying which aspects of urban planning and transportation management can benefit the most from MaaS data.
4. **Real-Life Scenarios:** Suggesting real-life use cases based on MaaS data provides tangible examples of how this data can be applied to address urban challenges. These use cases serve as practical templates for implementing data-driven solutions in complex urban environments.

In summary, the study on MaaS data exploitation contributes to handling complex urban data processes by providing structure and purpose to the data. It aids in stakeholder alignment, assessment of data usability, and the development of actionable strategies for using MaaS data to advance sustainability and address urban challenges. This approach enhances the effectiveness of smart city systems and decision-making processes within urban planning.

c. Big Data Loop for Smart City System Optimization

The Big Data Loop is a cyclical process designed to enhance the efficiency and effectiveness of smart city systems (Bibri, 2021). It consists of three main stages: data acquisition, data analysis, and feedback. In the data acquisition stage, data from various sources, such as sensors and connected devices, is collected, and stored. In the data analysis stage, machine learning algorithms are applied to extract insights and patterns from this data. These insights are then used to optimize various aspects of smart city operations, including transportation, energy, and public services (H. Liu, 2023). Finally, in the feedback stage, the optimized operations are implemented, and their performance is continuously monitored to generate new data. This new data is fed back into the loop, allowing the system to adapt and improve over time, ultimately leading to greater efficiency, cost savings, and better outcomes for citizens. The study can meaningfully contribute to the effectiveness of the Big Data Loop for automated smart city system optimization. Here is how:

1. **Enhanced data acquisition:** The study can help identify various sources of MaaS data, such as user behavior, transportation usage patterns, and mobility preferences. By understanding these data sources, city planners can improve data acquisition strategies within the Big Data Loop, ensuring a comprehensive and continuous influx of valuable information.
2. **Advanced data analysis:** The study's focus on clustering MaaS data types and defining stakeholders for SDG goals aligns with the data analysis stage of the Big Data Loop. Machine learning algorithms can leverage the insights derived from this study to better understand user behavior and transportation trends. This, in turn, enhances the efficiency of data analysis, enabling the extraction of more meaningful insights from the collected data.
3. **Optimized MaaS operations:** The insights and patterns identified through the study can directly contribute to the optimization of MaaS operations, including route planning, vehicle dispatching, and fare pricing. The Big Data Loop can utilize these insights to make real-time adjustments, improving the overall efficiency and effectiveness of the smart city's transportation services.
4. **Continuous learning and adaptation:** The study's emphasis on continuous learning aligns with the core concept of the Big Data Loop. By integrating the study's findings, the MaaS system can adapt and evolve over time, ensuring it remains responsive to changing citizen needs and preferences. This adaptability results in a self-optimizing system that consistently improves its services.
5. **Proactive issue identification:** The Big Data Loop's feedback stage, which monitors the performance of optimized MaaS operations, can benefit from the

study's insights. By analyzing data generated during the feedback stage, the system can identify emerging issues and address them proactively. This proactive approach enhances governance and service delivery by preventing major problems and disruptions.

In conclusion, the findings of this study on MaaS data exploitation can contribute by providing an introductory understanding of how MaaS data can be leveraged to achieve urban development objectives. It equips the Big Data Loop within the automated smart city system with the knowledge and insights needed to continuously optimize MaaS operations, improve citizen services, and proactively address emerging challenges.

7.4 LIMITATIONS

The present research attempts to center its attention and engage with the various facets of urban planning that are related to MaaS data. The scope of this study, however, does not encompass the precise definition of individual keywords, nor does it delve into their detailed implementation. Rather, it aims to assess the correlation between them, measure their potential for applicability and implication, and determine their level of compatibility. Nonetheless, the intricate linkage between each keyword, its derivation and source, and its corresponding city planning application presents a more arduous task that necessitates the collective expertise of professionals from diverse fields and an extensive timeframe for delivering conclusive outcomes.

It is envisaged that further examination will be necessary concerning the opportunities and challenges that are associated with the diverse tiers of MaaS. Such an inquiry holds significant importance in ascertaining the consequential impacts that can be realized through the deployment of various MaaS services in relation to factors such as social welfare, economic viability, ecological sustainability, and business prospects. This additional analysis will aid in comprehending the full spectrum of potential outcomes that may result from the implementation of distinct levels of MaaS and, consequently, inform strategic decision-making with regard to the optimization of MaaS services for the betterment of society and the environment as well as for the attainment of commercial objectives.

Despite the findings of the study shedding light on various aspects of the relationship between people's mobility patterns, smart mobility features, and interpersonal interactions, there exists a general limitation that can be attributed to the use of correlational methods. While these methods are useful for identifying associations between exposure and consequences, they are incapable of identifying causation. The study required extensive efforts and more time to collect, organize, synchronize, and analyze large datasets on mobility, culminating in the derivation of concrete and measurable indices. Nevertheless, recent literature indicates that more efficient tools, such as AI techniques and advanced Big Data Analytics, can handle such topics with greater speed, accuracy, and capacity to include larger datasets.

Whilst NLP has undergone significant advancements, its widespread implementation remains somewhat limited. The proficiency of current methodologies in deciphering natural language falls short of human capabilities. Coping with intricacies such as linguistic, cognitive, anthropological, and sociocultural nuances poses more challenges for NLP. Indeed, such complexities often prove daunting, even for experienced human analysts. Hence, NLP must continue to improve its ability to handle these intricacies if it is to become a more effective tool for processing natural language.

7.5 RECOMMENDATIONS

- Establishing a guideline for identifying appropriate strategies tailored to specific contexts represents a positive step toward enhancing urban mobility systems. However, it is important to acknowledge that each city and mobility system possesses distinct characteristics and requirements, which may necessitate the formulation of unique and customized strategies. Hence, it is imperative to bear in mind that although this study examined a restricted number of MaaS platforms, its findings cannot be extrapolated to all MaaS scenarios. Consequently, conducting locally focused studies utilizing the same approach may yield more dependable results.
- Achieving an all-encompassing MaaS system necessitates a greater commitment towards the implementation of MaaS services that are accessible to all users, irrespective of their backgrounds or abilities (Dadashzadeh et al., 2022), targeting vulnerable social groups, namely elderly people, people with disabilities, and low-income populations. Such targeted efforts produce more tangible outcomes, resulting in the development of more robust and efficient MaaS systems. Consequently, this contributes towards the creation of cities

that are realistically livable, where all members of society can access and benefit from the provided services.

- Enabling the implementation of MaaS, particularly in developing countries, necessitates the establishment of sturdy foundations at the social, economic, and institutional levels. In this regard, a greater emphasis on the user, who represents the central cog in the MaaS system, is necessary, such as convincing people to forgo personal vehicle usage. Illustrative initiatives such as the 9-Euro ticket in Germany 2022 (Loder et al., 2022) exemplify this approach.
- Efforts by organizations such as MaaS Alliance to bridge gaps between disparate approaches and develop standardization and harmonization solutions that benefit all stakeholders are crucial. However, research in this direction can only be effective and have a tangible impact if MaaS models share the same overarching principles. The creation of new standards or the reinvention of existing ones can reduce the benefits of such initiatives and restrict the potential for the exchange and contribution of experiences.
- It is important to strike a balance between preserving the business interests of stakeholders and ensuring that anonymized and aggregated data generated by the MaaS ecosystem is made available for various purposes, including but not limited to transport planning and urban planning. By enabling access to this data, policymakers and other relevant parties can make informed decisions that positively impact the mobility and livability of cities.
- It is incumbent upon legislative bodies to furnish additional textual provisions that correspond to the exigencies of the end-users, particularly those that pertain to the capability of evaluating the degree of safety and safeguarding of the user through the utilization of the application. Moreover, the feedback provided by users shall be communicated to the relevant stakeholders and harnessed to augment the level of safety and security of the system.
- It is imperative that consumers are furnished with clear and comprehensive data regarding MaaS offerings before signing up. Inclusive of the terms and conditions governing their utilization. Providing transparent information can foster trust and confidence among consumers, which is essential for the successful implementation and adoption of new mobility solutions.

Additionally, it leads to greater accountability and responsibility on the part of service providers to be held accountable for any failures to deliver on their promises, which can ultimately drive the development of better and more reliable services.

- The support and facilitation of new MaaS pilot programs to gather data and conduct additional research on user travel behavior and preferences for market segmentation are essential to address the primary challenges facing the development of MaaS solutions. The impact of the COVID-19 pandemic on the feedback provided by MaaS pilots over the past few years needs to be considered. The pandemic has led to significant changes in travel behavior, with many people working remotely and reducing their overall travel. This has affected the demand for and utilization of MaaS services, and it is important to assess how these changes may have impacted the feedback provided by users. Therefore, supporting new MaaS pilots and conducting additional research on user travel behavior and preferences after the pandemic, along with the new normal conditions, will provide good insights for future developments.
- Assessing the potential of MaaS to alter travel behavior is critical to understanding the impact of these services on urban mobility and sustainability. MaaS has the potential to provide users with a seamless and convenient travel experience and may encourage people to use more sustainable modes of transport. However, the effectiveness of MaaS in achieving these goals depends on a range of factors, including the availability and reliability of services, pricing, and user acceptance. Evaluating the advantages and drawbacks of the services provided by MaaS is equally important.
- Recent advancements in the field of NLP, particularly with the development of pre-trained and AI models, have shown significant potential for transforming the way textual data is analyzed and implied. While this may encourage more academics to incorporate NLP techniques in their research, it is important to consider the limitations of NLP and the potential impact on research outcomes. Although pre-trained models offer many advantages over traditional methods, it is still important to compare the results of NLP analysis to those obtained using more conventional techniques. This is because pre-trained models may

not always be effective in capturing the nuances and complexities of language use and may not be suitable for all types of text analysis tasks.

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Excursive Chapter: Impact of COVID on MaaS

The year 2020 witnessed an unprecedented global upheaval with the outbreak of the COVID-19 pandemic, significantly impacting various aspects of human life (Wilder-Smith et al., 2020). The transportation sector, particularly MaaS, underwent a notable transformation as authorities and individuals grappled with containing the virus's transmission (Askarizad et al., 2021). MaaS encountered distinct challenges and opportunities during the pandemic (de Palma et al., 2022).

This study examines the mobility patterns of individuals in Germany during the COVID-19 pandemic. Using a large dataset, the impact of smart mobility indices on mobility trends and interpersonal contacts is assessed. The research covers the pandemic period from 2019 to mid-2022, identifying distinct travel patterns for each wave of the crisis. The data collection process, presented in section 1, includes COVID-19 Community Mobility Reports from Google, Smart Mobility Index data from Bitkom e.V. reports, and the Contacts between individuals. This is followed by section 6, which examines the possible relationships among Mobility Trends (MT), Smart Mobility Index (SMI), and individual contact (IC), highlighting their interconnectedness through various models, such as correlated covariates, independent covariates, spurious relationships, mediation, and moderation, to help interpret the results of the correlation study.

Section 7 highlights the Pearson correlation findings for the phases of the pandemic. These matrices are devised using three significant factors and their respective sub-elements. In addition, a graphic representation of correlation values is employed for analysis and authentication of the linkage among smart urban mobility, mobility tendencies, and human contact.

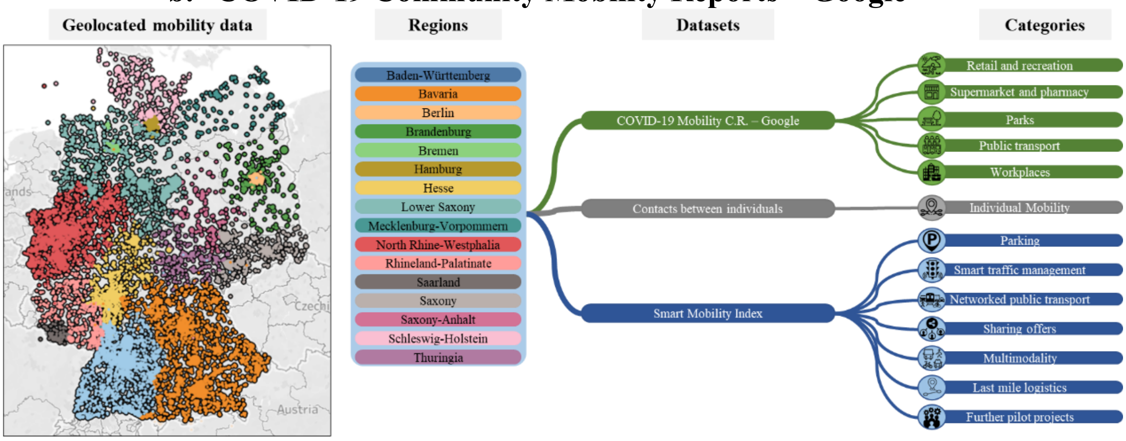
1. DATA AND METHODOLOGY

In this study, a large dataset is utilized to examine individuals' everyday mobility patterns, drawing a sample from various regions across Germany. The correlation coefficient matrix is then employed to assess the impact of smart mobility indices on mobility trends, as well as the number of interpersonal contacts. The study encompasses the entirety of the pandemic period, spanning from 2019 to the middle of 2022, and thus identifies distinct travel mobility patterns for each wave of the crisis. As shown in Fig. 25. The analysis process includes several steps alongside data collection, processing, and analysis, all of which are elaborated upon in greater detail in the subsequent sections.

Fig. 25. Data analysis process, geolocation, abstraction by region, datasets, and categories. By the author.

With the study's defined geographical scope as Germany, comprising its sixteen partly sovereign federated states, the subsequent phase is the delineation of datasets, elucidated as follows:

b. COVID-19 Community Mobility Reports – Google



The CMR data is obtained in the form of a CSV file containing comma-separated values and covering more than 135 countries, with some regions providing more detailed information. The data is collected from individuals who have voluntarily opted to share their location history and is made anonymous to protect their privacy (Aktay et al., 2020). The per-locality data provided by CMR consists of six time series that correspond to various categories of places created by Google, as detailed in section x. Each time series covers a duration of one year, starting from February 15th, 2020, to December 31st, 2020, for the first year and January 1st, 2021, to December 31st, 2021, for the second year. The value for a particular timestamp and category is calculated in relation to a baseline, which is the median value for the corresponding day of the week during the period between January 3rd, 2020, and February 6th, 2020 (Google, 2022).

The data shows how visits to places are changing in each geographic region in Germany (Baden-Wurttemberg, Bavaria, Berlin, Brandenburg, Bremen, Hamburg, Hessen, Lower-Saxony, Mecklenburg-Vorpommern, North Rhine-Westphalia, Rhineland-Palatinate, Saarland, Saxony, Saxony-Anhalt, Schleswig-Holstein, Thuringia) over two years (2020, 2021 and mid-2022). Changes for each day are compared to a baseline value for that day of the week. The baseline is the median value for the corresponding day of the week during the five weeks.

Table 11. Place Category Descriptions from Google CMR (Google LLC, 2020)

Category	Places
Retail and recreation	Restaurants, cafés, shopping centers, museums, libraries, and cinemas.
Supermarket and pharmacy	Supermarkets, food warehouses, farmers markets, food shops and pharmacies.
Parks	National parks, public beaches, marinas, dog parks, plazas, and public gardens.
Public transport	PT hubs, such as underground, bus and train stations
Workplaces	Places of work

Locality-wise calibrated CMR data is used and processed through seasonal-trend decomposition. The period of the research starts at the beginning of 2020 and continues to the middle of 2022. To define the extent of each phase, the mandatory notification data was used on SARS-CoV-2 cases in Germany (Schilling et al., 2021), giving five different pandemic stages of SARS-CoV:

- The first wave (CW 9/2020, March 2020 -CW 28/2020, July 2020)
- The second wave (CW 29/2020, July 2020 - CW 5/2021, February 2021)
- The third wave (CW 6/2021, February 2021 - CW 25/2021, June 2021)
- The fourth wave (CW 26/2021, June 2021 - CW 37/2021, September 2021)
- And the post-pandemic period (CW 41/2021, October 2021 - CW 26/2022, June 2022)

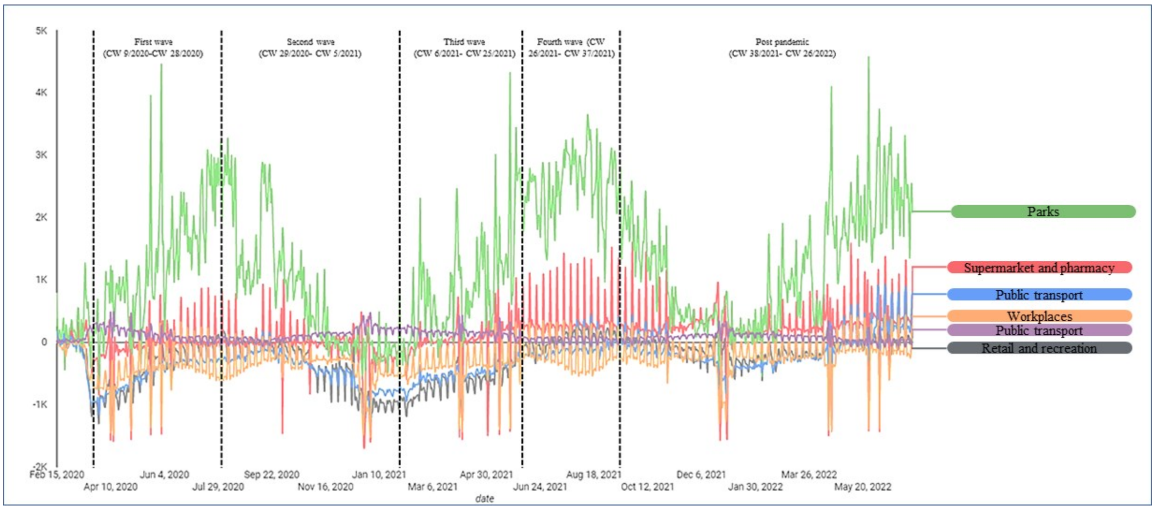


Fig. 26. Original CMR data for Germany. Vertical Dashed Lines Indicate Periods from each COVID-19 Wave Start/Finish, from March 2020 until June 2022.

c. Smart Mobility Index

Within Bitkom e.V. reports for the Smart City Index for 2020 and 2021, the digital ranking of major German cities was explored to inform about the status quo, developments, and trends. With more than 11,000 data points recorded, checked, and qualified, 81 cities with at least 100,000 inhabitants were analyzed and rated in the five subject areas of administration, IT and telecommunications infrastructure, energy and the environment, mobility, and society. The reports give good insights into the advancement of the overall smart city applications in different cities and regions in Germany, see Fig 27. For this study, the focus is mainly on the data related to smart mobility and took the following indices:

- **Parking:** Smart parking, Cell phone parking
- **Smart traffic management**: Intelligent traffic lights, Digital traffic signs, Automated counts
- **Networked PT:** Cell phone tickets, Real-time information, Free Wi-Fi, Autonomous vehicles
- **Sharing offers:** Car sharing (number of vehicles per 1,000 inhabitants, e-cars), Bike sharing (offer available, e-bikes), Ridesharing (ride pooling, on-demand traffic, Commuter/passenger portal), and E-scooter sharing.
- **Multimodality:** Multimodal app (offer available, app rating), Mobility stations, Modal split
- **Last mile logistics:** Micro hubs/city hubs, Alternative delivery, Cross-provider parcel stations

- **Further pilot projects**

Defining data related to MaaS levels is a challenging task, particularly regarding MaaS integration levels. While the existence of the MaaS system cannot be denied, it cannot be used as a reference for MaaS. This study focuses on shared mobility, multimodality, and mobility on transits as factors that refer to MaaS usage at various levels. However, other factors are also analyzed and covered in the study to examine mobility trends during the pandemic.

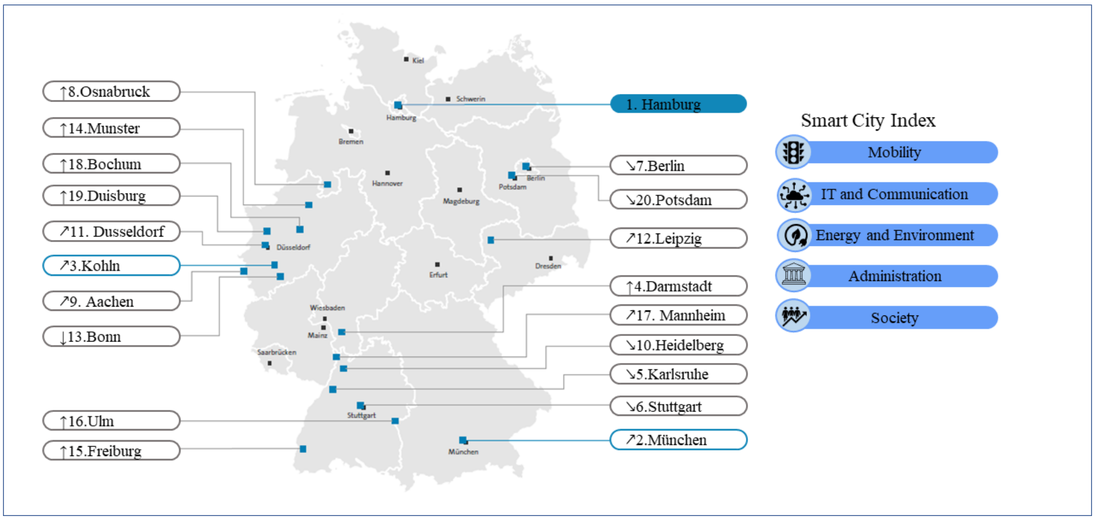


Fig 27. Top 20 Smart City Index 2021, based on data from Bitkom e.V.

d. Contacts between individuals

The mode of transportation that individuals utilize can vary, especially with the emergence of new mobility options (Luh et al., 2022). Nevertheless, it is widely acknowledged that human-to-human contact remains the primary mode of disease transmission (Rana et al., 2022), particularly when individuals share a confined space for an extended period (Liu, Kortoçi, et al., 2022) and come into contact with one another (X. Liu, Kortoçi, et al., 2022).

However, this measure is not entirely reliable, as all contacts do not pose the same level of risk of infection. For instance, a hug between two elderly individuals who are not part of the same household and have no other risk factors may pose a higher risk of infection than a brief handshake between two individuals who are both fully vaccinated and asymptomatic (Fields et al., 2021). The number of contacts, referred to as contact intensity, is a crucial parameter in the transmission of infectious diseases (X. Liu, Dou, et al., 2022): the more contacts an individual has, the greater the likelihood of the pathogen spreading.

GPS is a technology used to track the location of mobile phones over time and indicates when people are close. Accordingly, it can derive how many contacts a person encounters. The location data are available, provided by the German company NET CHECK from cell phones, but the exact measures are not accessible. The number of contacts is used as a proxy for social life activity, with a focus on the number of contacts each day. Around 1.2 million devices (about 50% active every day) in Germany are equipped with a Software Development Kit SDK to generate GPS data. All the users were informed and agreed to collect the data (that does not contain any personal information) for statistical purposes. Several hundred locations are transmitting per day for each device.

The data for this study is GIS-based; each row is affiliated to a location within the German territory, classified by region, and associated with the datasets selected for the mobility analysis. The datasets are divided into the mentioned categories and opted for the most relevant trends and indices; this classification also allows the recognition of the impact of each factor. Fig. 25. illustrates the overall process of the data analysis in this study.

6. THE INTERCONNECTION AMONG THE VARIABLES

As mentioned earlier in the research design, three key variables are under consideration: Mobility Trends (MT), Smart Mobility Index (SMI), and Individuals Contact (IC). Among these variables, MT serves as the dependent variable, whereas SMI and IC act as the independent predictors. Here are possible connections among these variables:

- **Correlated Covariate with Mobility Trends**

In this model, the covariate MT is correlated with SMI, and both predict IC. Since MT and SMI are interdependent, there will often be some aspect of their association that cannot be differentiated from their relationship with IC.

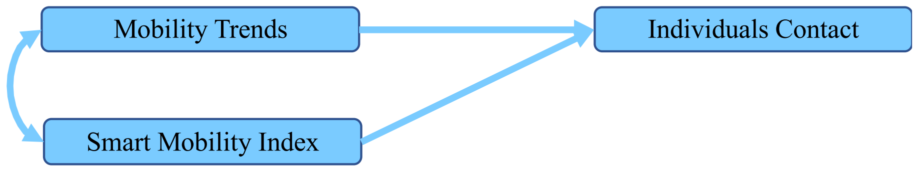


Fig. 28. Correlated Covariate with Mobility Trends. Source: The Author.

The whole impact of MT on IC is no longer represented by the link between SMI and IC. After accounting for the impact of IC, it is the one-off effect of MT on IC. The regression coefficient for MT will only consider its unique influence, while the model factor in both the joint and the unique effects of both MT and SMI on IC. It is nevertheless conceivable to gauge MT's particular impact if the connection is moderate. However, if it rises too high, the model will begin to reach a threshold of multicollinearity where it will be difficult to make estimations.

This kind of association can be seen, for instance, in research that examines lower elevations (MT) typically having more impact since the other factor (SMI) is downwards. As a result, the specific impact of IC can be detected if their correlation is only mild. By combining MT and SMI in a model, the impact can be investigated. Rerunning the model without IC and observing how much MT's coefficient changes can help to determine the extent to which SMI and MT overlap in their explanation of IC.

- **Independent Covariate by Mobility Trends**

A covariate SMI has a slightly different impact when it is not related to MT. To be effective in the model, it must be able to forecast IC, but the impact of MT and SMI are not combined.

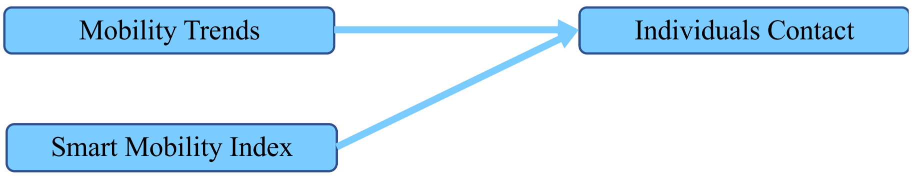


Fig. 29. Independent Covariate by Mobility Trends. Source: the author.

SMI frequently explains part of the otherwise unexplained variance in IC, which causes the relationship between MT and IC to become more significant when SMI is included in the model.

When a variant is considered, it is no longer considered random and is eliminated from the denominator. Running the hierarchical regression is recommended for this case to examine this kind of effect and add each predictor in a separate step.

- **Spurious Relationship with Mobility Trends**

Because SMI is connected to both MT and IC, it produces a false relationship between MT and IC.

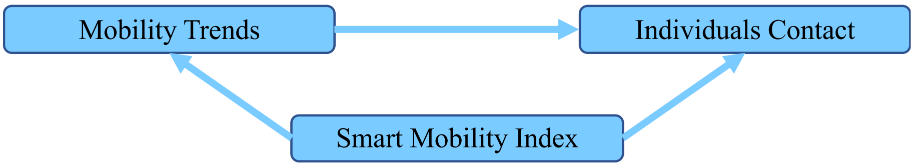


Fig. 30. Spurious Relationship with Mobility Trends. Source: The Author.

In the context of the pandemic, a spurious correlation may be observed between decreased urban mobility and lower infection rates. This means that the apparent relationship between these variables is misleading and not causally connected. Other factors, such as the implementation of social distancing measures or the adoption of remote work policies, could be responsible for both reduced mobility and the decline in infection rates. Thus, the observed correlation is a result of the influence of these confounding factors, and it is essential to recognize this spuriousness when interpreting the relationship between urban mobility changes and the pandemic's impact on infection rates.

- **Mediation**

Mediation points to a certain causal chain. It happens when SMI is at least somewhat responsible for how MT impacts IC. MT impacts SMI, and SMI impacts IC.

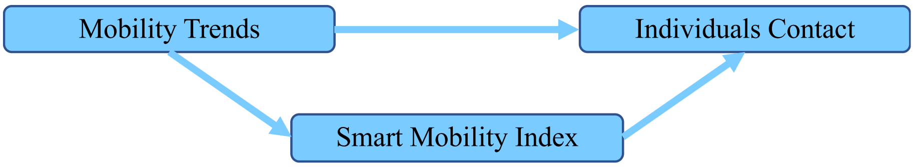


Fig. 31. Mediation of Mobility Trends, Smart Mobility Index, and Individual Contacts. Source: The Author.

The two factors of MT on SMI are the direct influence of MT on IC and the indirect effect of MT on IC through SMI. If high Smart Mobility Indices (SMI) were the link between stress Mobility Trends and the Contacts between Individuals, this would be demonstrated with the variation of the Smart Mobility Indices.

Testing for mediation can be accomplished in many ways, mainly by using path analysis or running regression model series. The new approaches suggest gauging the strength of the indirect factor first.

- **Moderation**

Despite their labels being similar, mediation and moderation are two very different things. Moderation signifies that MT has a varying impact on IC for different values of SMI. SMI, therefore, impacts (moderates) the impact of MT on IC.

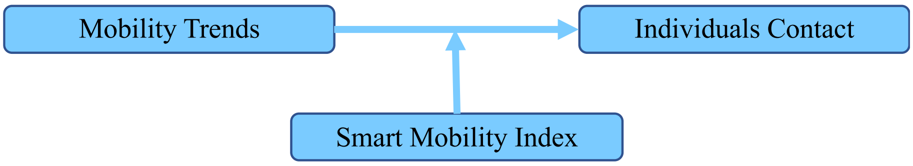


Fig. 32. Moderation of Mobility Trends, Smart Mobility Index, and Individual Contacts. Source: The Author.

Often, when SMI has a minor effect, there will be no impact of MT on IC, but there would be when SMI is large and between MT and IC. By considering MT/IC correlated, moderation can be tested. The association with the third factor, SMI, can be retrieved, and accordingly, the values will be predicted. Presumably, the value of MT/SMI can predict IC in various ways depending on the value of MT and SMI and if they are connected or not.

The correlation between MT, SMI, and the IC is one instance of moderation contact between people. If there was a small negative association among cities with low Smart Mobility Indices but a huge negative association among those with high SMI, it would be considered to mitigate the relationship between the MT and IC.

The forthcoming section will focus on data analysis, the investigation of potential inter-variable relationships, and the interpretation of findings. These stages are expected to yield wider perspectives for the research and enhance comprehension of current MaaS patterns.

7. EXPLORING THE MOBILITY SYSTEM IMPACT THROUGH CORRELATION COEFFICIENTS

The present study utilizes correlation coefficients as a tool to ascertain the degree of linear relationship between pairs of variables selected from the datasets under investigation. Correlation coefficients are used to measure the strength of association between two variables, with values greater than zero being denoted by the color green to signify a positive relationship, while values less than zero are represented by the color red to indicate a negative relationship. A value of zero signifies no correlation between the two variables being compared, with the intensity of the color diminishing as the value approaches zero.

To illustrate, a positive correlation between mobility sharing offers and mobility to workplaces suggests that an increase in the former leads to a greater number of individuals commuting to work. On the other hand, a negative correlation between smart traffic management and mobility within transit stations suggests that people are less likely to use transit stations in cities with underprivileged traffic management systems. By employing this method, the study aims to uncover meaningful insights into the relationships between the variables and to determine the degree and direction of the association between them. Of particular interest is the region demarcated by the red contours, which denotes the intersection of the analyzed variables. This focal point serves as the nexus for computer correlations, affording an enhanced understanding of the intricate relationships between mobility and social connectivity.

Thereby, the Pearson correlation coefficient is calculated for each of the five periods of COVID-19. Figures Fig. 33, Fig 34, Fig. 35, Fig. 36, and Fig. 37 highlight a significant correlation between the deployment of smart mobility systems and the alteration of urban mobility patterns.

- **The first wave**

The results show that there is a positive correlation between the mobility smart index and mobility during the pandemic, with the highest correlation coefficient observed for transit stations (0.781), followed by workplaces (0.653) and retail and recreation (0.617). This suggests that the deployment of smart mobility systems can influence and shape the way people move and travel during the pandemic.

Furthermore, the correlation coefficients between the mobility-related factors and the number of contacts between people show that there is a strong positive correlation between the number of contacts and mobility at transit stations (0.781), followed by workplaces (0.653). This indicates that the use of public transportation and commuting to work may increase the likelihood of contact between people, which can potentially lead to the spread of the virus.

In contrast, there is a negative correlation between the mobility smart index and various mobility-related factors such as sharing offers, multimodality, last-mile logistics, networked public transport, and smart traffic management, suggesting that the deployment of smart mobility systems may have a mitigating effect on the spread of the virus. The overall correlation coefficient between the mobility smart index and the number of contacts is -0.025, indicating a weak negative correlation.

		Mobility Trends					N-C	Smart mobility index						Overall
		R&R	G&Ph	P	T.S	Wo		Pa	STM	NPT	SO	Mu	LML	
Mobility Trends	Retail and recreation	1												
	Grocery and pharmacy	0,507	1,000											
	Parks	0,392	0,179	1,000										
	Transit stations	0,767	0,508	0,349	1,000									
	Workplaces	0,889	0,460	0,281	0,845	1,000								
Number of Contacts		0,617	0,592	0,341	0,781	0,653	1,000							
Smart M. index	Parking	-0,280	0,009	0,242	-0,179	-0,330	0,136	1,000						
	Smart traffic management	-0,410	0,128	0,068	-0,286	-0,388	-0,029	0,207	1,000					
	Networked public transport	-0,522	0,277	-0,140	-0,357	-0,411	-0,208	0,298	0,661	1,000				
	Sharing offers	-0,759	-0,187	-0,246	-0,450	-0,701	-0,265	0,490	0,446	0,717	1,000			
	Multimodality	-0,691	0,136	-0,231	-0,237	-0,513	-0,020	0,455	0,545	0,765	0,824	1,000		
	Last mile logistics	-0,561	0,204	-0,382	-0,260	-0,363	-0,012	-0,012	0,518	0,640	0,516	0,761	1,000	
Overall		-0,680	0,132	-0,145	-0,332	-0,548	-0,025	0,525	0,717	0,828	0,818	0,951	0,772	1,000

Fig. 33. Correlation Matrix of Mobility Advancement Impact on the Mobility Trends and the Contact Between People of COVID-19, the First Wave. Source: The Author.

- **The second wave**

The results show that there is a significant negative correlation between the SMI and mobility during the pandemic, as well as between the SMI and the number of contacts between people. This suggests that the deployment of smart mobility systems has a crucial role in shaping the way people practice urban mobility during the pandemic, which has led to a reduction in the number of people's contacts.

Furthermore, there is a negative correlation between the SMI and all the mobility indicators, i.e., retail and recreation, grocery and pharmacy, parks, transit stations, and workplaces. This finding suggests that the deployment of smart mobility systems has led to a reduction in mobility in various settings.

In terms of the specific smart mobility systems, the data reveals that all systems have a negative correlation with mobility and contacts. Among these, networked public transport and sharing offers have the strongest negative correlation with mobility and contacts. In contrast, last-mile logistics has the weakest negative correlation.

Finally, the overall negative correlation between SMI and mobility/contact reinforces the significant role played by smart mobility in shaping urban mobility patterns during the pandemic.

		Mobility Trends					N-C	Smart mobility index						Overall
		R&R	G&Ph	P	T.S	Wo		Pa	STM	NPT	SO	Mu	LML	
Mobility Trends	Retail and recreation	1,000												
	Grocery and pharmacy	0,907	1,000											
	Parks	0,854	0,907	1,000										
	Transit stations	0,888	0,799	0,745	1,000									
	Workplaces	0,835	0,629	0,580	0,871	1,000								
Number of Contacts		-0,509	-0,372	-0,523	-0,657	-0,601	1,000							
Smart M. index	Parking	-0,052	-0,016	0,084	-0,130	-0,281	0,093	1,000						
	Smart traffic management	-0,510	-0,412	-0,378	-0,513	-0,491	0,246	0,207	1,000					
	Networked public transport	-0,632	-0,486	-0,504	-0,507	-0,585	0,150	0,298	0,661	1,000				
	Sharing offers	-0,578	-0,347	-0,273	-0,471	-0,759	0,260	0,490	0,446	0,717	1,000			
	Multimodality	-0,465	-0,228	-0,239	-0,338	-0,630	0,144	0,455	0,545	0,765	0,824	1,000		
	Last mile logistics	-0,390	-0,146	-0,301	-0,326	-0,489	0,139	-0,012	0,518	0,640	0,516	0,761	1,000	
Overall		-0,494	-0,274	-0,282	-0,428	-0,653	0,197	0,525	0,717	0,828	0,818	0,951	0,772	1,000

Fig 34. Correlation Matrix of Mobility Advancement Impact on the Mobility Trends and the Contact Between People of COVID-19, the Second Wave. Source: The Author

- **The third wave**

The correlation coefficients suggest that there is a strong positive relationship between the number of contacts and mobility in retail and recreation areas, grocery and pharmacy stores, parks, and transit stations. These coefficients are 0.631, 0.617, 0.311, and 0.683, respectively. It indicates that as mobility increases in these places, the number of contacts between people also increases.

On the other hand, there is a negative correlation between the smart mobility index and mobility during the pandemic. The coefficients for smart traffic management, networked public transport, sharing offers, and overall smart mobility are negative (-0.464, -0.637, -0.794, and -0.655, respectively), indicating that the deployment of smart mobility systems is associated with a reduction in mobility during the pandemic.

Further, the coefficient for sharing offers and overall smart mobility is highly negative (-0.898 and -0.770, respectively), suggesting that the implementation of smart mobility systems that enable shared transport options can result in a substantial reduction in mobility during the pandemic.

Moreover, there is a negative correlation between the number of contacts and the different aspects of smart mobility. The coefficients for sharing offers, networked public transport, and last-mile logistics are -0.530, -0.466, and -0.209, respectively, indicating that the implementation of these aspects of smart mobility can reduce the number of contacts between people.

		Mobility Trends					N-C	Smart mobility index						Overall
		R&R	G&Ph	P	T.S	Wo		Pa	STM	NPT	SO	Mu	LML	
Mobility Trends	Retail and recreation	1,000												
	Grocery and pharmacy	0,728	1,000											
	Parks	0,506	0,676	1,000										
	Transit stations	0,789	0,496	0,405	1,000									
	Workplaces	0,839	0,490	0,249	0,795	1,000								
Number of Contacts		0,631	0,617	0,311	0,683	0,462	1,000							
Smart M. index	Parking	0,250	0,351	0,415	0,105	0,153	-0,201	1,000						
	Smart traffic management	-0,464	-0,314	-0,326	-0,434	-0,566	-0,112	-0,253	1,000					
	Networked public transport	-0,637	-0,538	-0,179	-0,406	-0,634	-0,466	-0,005	0,436	1,000				
	Sharing offers	-0,794	-0,558	-0,196	-0,640	-0,898	-0,530	-0,086	0,619	0,791	1,000			
	Multimodality	-0,192	0,037	0,063	-0,361	-0,277	-0,393	0,551	0,367	0,401	0,339	1,000		
	Last mile logistics	-0,264	0,124	-0,060	-0,452	-0,281	-0,209	0,412	0,356	0,311	0,218	0,749	1,000	
Overall		-0,655	-0,398	-0,333	-0,569	-0,770	-0,407	0,051	0,766	0,764	0,799	0,575	0,509	1,000

Fig. 35. Correlation matrix of Mobility Advancement Impact on the Mobility Trends and the Contact Between People of COVID-19, the Third Wave. Source: The Author

- **The fourth wave**

The strongest positive correlation coefficient is found between the number of contacts and mobility in retail and recreation areas (0.692), followed closely by grocery and pharmacy areas (0.719). There is also a moderately positive correlation between the number of contacts and parks (0.605) and transit stations (0.582). The weakest correlation is found between the number of contacts and workplaces (0.483).

In terms of the smart mobility index, there is a strong negative correlation between smart traffic management and all areas of mobility during the pandemic. Networked public transport and sharing offers also exhibit a strong negative correlation with all areas of mobility during the pandemic. Multimodality and last-mile logistics show weaker negative correlations.

Overall, the results suggest that the smart mobility index is negatively associated with mobility during the pandemic and the number of contacts. The strongest negative correlation is found between the overall smart mobility index and workplaces (-0.656), followed by transit stations (-0.576) and retail and recreation (-0.591). Grocery and pharmacy areas show a weaker negative correlation (-0.427), while parks exhibit the weakest negative correlation (-0.428).

		Mobility Trends					N-C	Smart mobility index						Overall
		R&R	G&Ph	P	T.S	Wo		Pa	STM	NPT	SO	Mu	LML	
Mobility Trends	Retail and recreation	1,000												
	Grocery and pharmacy	0,927	1,000											
	Parks	0,928	0,971	1,000										
	Transit stations	0,935	0,872	0,881	1,000									
	Workplaces	0,781	0,636	0,615	0,865	1,000								
Number of Contacts		0,692	0,719	0,605	0,582	0,483	1,000							
Smart M. index	Parking	0,115	0,076	0,109	0,110	0,039	-0,211	1,000						
	Smart traffic management	-0,559	-0,422	-0,461	-0,569	-0,500	-0,052	-0,253	1,000					
	Networked public transport	-0,505	-0,381	-0,278	-0,405	-0,529	-0,378	-0,005	0,436	1,000				
	Sharing offers	-0,651	-0,438	-0,405	-0,616	-0,801	-0,363	-0,086	0,619	0,791	1,000			
	Multimodality	-0,143	-0,097	-0,070	-0,261	-0,305	0,027	0,551	0,367	0,401	0,339	1,000		
	Last mile logistics	-0,273	-0,186	-0,201	-0,356	-0,312	0,057	0,412	0,356	0,311	0,218	0,749	1,000	
Overall		-0,591	-0,427	-0,428	-0,576	-0,656	-0,157	0,051	0,766	0,764	0,799	0,575	0,509	1,000

Fig. 36. Correlation matrix of Mobility Advancement Impact on the Mobility Trends and the Contact Between People of COVID-19, the Fourth Wave. Source: The Author.

- **The post-pandemic**

The results suggest that the smart mobility index has a significant negative correlation with mobility during the pandemic in all categories, with the highest correlation coefficient being -0.820 with Sharing Offers. This indicates that the deployment of smart mobility systems may have contributed to reducing the overall mobility of people during the pandemic.

Additionally, the data also shows a strong negative correlation between the smart mobility index and the number of contacts between people, with a correlation coefficient of -0.599. This implies that the use of smart mobility systems may have led to a reduction in the number of interpersonal contacts during the pandemic.

Moreover, the correlation matrix reveals a negative relationship between the smart mobility index and various mobility categories, such as Retail and recreation, Parks, Transit stations, and Workplaces. This finding suggests that the deployment of smart mobility systems may have led to a decline in mobility in these categories during the pandemic.

On the other hand, the data shows a positive correlation between Parking and the number of contacts between people. This result indicates that the availability of parking spaces may have contributed to an increase in interpersonal contacts during the pandemic.

		Mobility Trends					N-C	Smart mobility index						Overall
		R&R	G&Ph	P	T.S	Wo		Pa	STM	NPT	SO	Mu	LML	
Mobility Trends	Retail and recreation	1,000												
	Grocery and pharmacy	0,809	1,000											
	Parks	0,815	0,860	1,000										
	Transit stations	0,822	0,625	0,732	1,000									
	Workplaces	0,816	0,575	0,618	0,819	1,000								
	Number of Contacts	-0,572	-0,229	-0,322	-0,597	-0,680	1,000							
Smart M. index	Parking	0,245	0,295	0,289	0,133	0,065	0,383	1,000						
	Smart traffic management	-0,625	-0,464	-0,616	-0,553	-0,586	0,343	-0,253	1,000					
	Networked public transport	-0,713	-0,548	-0,366	-0,421	-0,627	0,467	-0,005	0,436	1,000				
	Sharing offers	-0,820	-0,565	-0,544	-0,664	-0,900	0,634	-0,086	0,619	0,791	1,000			
	Multimodality	-0,174	0,012	-0,048	-0,328	-0,299	0,484	0,551	0,367	0,401	0,339	1,000		
	Last mile logistics	-0,237	-0,035	-0,113	-0,343	-0,265	0,658	0,412	0,356	0,311	0,218	0,749	1,000	
	Overall	-0,726	-0,545	-0,569	-0,612	-0,787	0,599	0,051	0,766	0,764	0,799	0,575	0,509	1,000

Fig. 37. Correlation Matrix of Mobility Advancement Impact on the Mobility Trends and the Contact Between People of COVID-19, the post-pandemic. Source: The Author.

In summation, the present chapter has expounded upon the data analysis concerning smart mobility systems during the COVID-19 pandemic. As evidenced by the results, the deployment of smart mobility systems has potentially facilitated a decrease in both overall mobility and interpersonal contact during the pandemic. Conversely, the availability of parking spaces may have led to an increase in interpersonal interactions. Further, the negative correlation between the smart mobility index and mobility categories, including retail and recreation, parks, transit stations, and workplaces, implies a probable decline in mobility in these categories during the pandemic due to smart mobility systems. These observations can offer an informative resource for policymakers and urban planners in their efforts to design and implement smart mobility systems for combatting pandemics and other crises. Moving forward, the succeeding chapter will explore the potential ramifications of these findings for the development and implementation of smart mobility systems.

8. DISCUSSION

During the COVID-19 pandemic, the use of smart mobility systems has gained significant attention to reduce the spread of the virus. This study attempted to explore the correlation between smart mobility systems and the mobility of people, as well as the number of interpersonal contacts during different stages of the pandemic.

During the initial phase of the pandemic, there was a positive correlation between the mobility smart index and mobility, particularly in transit stations, workplaces, and retail and recreation areas. However, the deployment of smart mobility systems, including sharing offers, multimodality, and smart traffic management, showed a negative correlation with the number of interpersonal contacts.

In the second wave, a significant negative correlation was observed between the smart mobility index and mobility, as well as the number of interpersonal contacts. This finding suggests that the deployment of smart mobility systems resulted in a reduction in mobility across various settings.

During the third and fourth waves, the study found that the disposition of smart mobility systems, such as shared transport options, substantially reduced mobility in different categories, and various aspects of smart mobility had a negative correlation with the number of interpersonal contacts.

Moreover, in the post-pandemic period, it was observed that smart mobility systems may have played a crucial role in reducing overall mobility during the pandemic. Furthermore, the use of smart mobility systems was negatively correlated with the number of interpersonal contacts, leading to a decrease in interpersonal contacts during the pandemic. Conversely, the availability of parking spaces showed a positive correlation with the number of interpersonal contacts, potentially leading to an increase in interpersonal contacts during the pandemic.

The study's implications suggest that smart mobility systems can play a critical role in reducing the spread of future pandemics by shaping urban mobility and social contacts. Policymakers and urban planners must adopt a proactive stance towards the implementation of smart mobility systems, which have the potential to enable shared transportation options and simultaneously reduce interpersonal contact to effectively mitigate the detrimental impact of pandemics that may arise in the future.

9. CONCLUSION

This study aims to provide a deeper understanding of the potential impacts of mobility advancement on people's mobility during a time of crisis. The substantial return to public transportation and ridesharing is a necessary but not a satisfactory condition, yet more efforts will be needed to enable a more hygienic shared mode environment. The shift in the behavior of urban mobility users could open new opportunities for more individualized services and options, such as Mobility as a Service, and enable many technologies to take place and play a big role in defining the future mobility picture.

Although the study could uncover several aspects of the relationship between the mobility of people, smart mobility features, and interpersonal contact, a general shortcoming can be derived from the employment of the correlational method, that it can identify associations between exposure and outcomes but cannot identify causes and cannot be taken to imply causation. The research required extensive work and a considerable period to gather, structure, synchronize, and analyze immense mobility datasets and derive conclusions with concrete and measurable indices, yet the recent literature suggests more efficient tools such as Machine Learning techniques and advanced Big Data Analytics to handle such topics with less time and more accuracy and capacity to include larger datasets. Despite the limitation of data availability, the research can also be generalized to a larger scale and to other countries to reveal more facts and perceive the subject from other perspectives.

Appendices

Appendix A -List of Publications with a Focus on MaaS

N	Title	Year	Origin	Type	Objective
1	Mobility as a Service - A Proposal for Action for the Public Administration, Case Helsinki	(Heikkilä, 2014)	Finland	Case reports	Identify the pivotal components that underpin MaaS and propose a comprehensive strategy for its implementation within the Helsinki context.
2	The impact of Mobility as a Service concept to land use in Finnish context	(Rantasila, 2015)	Finland	Case reports	Analyzes MaaS effects on land planning.
3	An innovative mobility service to facilitate changes in travel behavior and mode choice	(Sochor et al., 2015)	Sweden	Empirical	Examines how using MaaS fulfills societal, commercial, and customers' requirements.
4	Developing the 'Service' in Mobility as a Service: Experiences from a Field Trial of an Innovative Travel Brokerage	(Karlsson et al., 2016)	Sweden	Case reports	Evaluates the case of UbiGo to define the main obstacles and enable further dissemination of MaaS
5	Conceptualizing Mobility as a Service	(Giesecke et al., 2016)	Monaco	Theorical	Presents evidence on cases of work in multi-disciplinary approaches for MaaS
6	Future bus transport contracts under a MaaS regime in the digital age: Are they likely to change?	(Hensher, 2017)	Australia	Conceptual	Presents several positions that represent the future contexts in which bus services might be offered
7	The potential of a Mobility-as-a-Service platform in a depopulating area in The Netherlands: An exploration of small and big data	(Geurs et al., 2018)	The Netherlands	Case reports	Evaluates whether a MaaS platform might be a practical and successful way to make rural places more accessible and livable.
8	Potential uptake and willingness-to-pay for Mobility as a Service (MaaS): A stated choice study	(Ho et al., 2018)	Australia	Empirical	Aims to understand the potential market of MaaS with an access to a range of mobility services
9	The Mobility as a Service Maturity Index: Preparing the Cities for the Mobility as a Service Era	(Kamargianni & Goulding, 2018)	UK	Theorical	Aims to develop a MaaS Maturity Index to measures city's readiness for MaaS implementation based on five dimensions
10	Mobility as a Service (MaaS) in the UK: Change and its Implications	(Enoch, 2018)	UK	Theorical	Explores perceived potential enablers, opportunities, barriers, and risks associated with using MaaS
11	Questioning mobility as a service: Unanticipated implications for society and governance	(Pangbourne et al., 2020)	UK	Conceptual	Presents a critical analysis of the rhetoric surrounding MaaS and focus on the development of its service model

12	Drivers and barriers in adopting Mobility as a Service (MaaS) – A latent class cluster analysis of attitudes	(Alonso-González et al., 2020)	The Netherlands	Empirical	Discusses the factors and the barriers related to MaaS adoption together with the policies that address them
13	The shape of MaaS: The potential for MaaS Lite	(Pickford & Chung, 2019)	Hong Kong	Case reports	Presents MaaS Lite, an incremental approach to MaaS and discusses its potential in Hong Kong and Brisbane
14	MaaS trends and policy-level initiatives in the EU	(Sakai, 2019)	Japan	Conceptual	Describes the MaaS concept in EU, the birth of the concept in Finland and its background, and EU-wide initiatives
15	Mobility as a Service (MaaS) and Sustainable Urban Mobility Planning. European Platform on Sustainable Urban Mobility Plan	(Rey-Moreno et al., 2020)	Belgium	Conceptual	Helps to understand what MaaS is, its opportunities and challenges
16	Urban Mobility Digitalization: Towards Mobility as a Service (MaaS)	(Barreto et al., 2018)	Portugal	Theorical	Presents the main platforms characteristics, regarding the European territory
17	A Case for Machine Learning in Edge-Oriented Computing to Enhance Mobility as a Service	(Carvalho et al., 2019)	Greece	Case reports	Shows can Edge-Oriented Computing and Machine Learning contribute to extending the reach of MaaS
18	Mobility as a service and sustainable travel behavior: A thematic analysis study	(Alyavina et al., 2020)	UK	Empirical	Discusses solutions on replacing private cars through MaaS alternatives and demonize private car ownership
19	MaaS bundle design and implementation: Lessons from the Sydney MaaS trial	(Ho et al., 2021)	Australia	Conceptual	Sets out a framework within which MaaS bundle design implementation is and introduced five types
20	Key barriers in MaaS development and implementation: Lessons learned from testing Corporate MaaS (CMaaS)	(X. Zhao et al., 2020)	Sweden	Conceptual	Identifies the development and implementation barriers of MaaS with an interdisciplinary approach
21	MaaS for the suburban market: Incorporating carpooling in the mix	(Wright et al., 2020)	UK	Case reports	Presents the results from a trial of the App in four European test sites to suggest trip planning solutions.
22	Mobility as a service (MaaS): Charting a future context	(Wong et al., 2020)	Australia	Conceptual	Proposes a government-contracted model for MaaS to push towards smaller and more flexible transport services
23	Limitations to the car-substitution effect of MaaS. Findings from a Belgian pilot study	(Storme et al., 2020)	Belgium	Empirical	Presents the results from an exploratory MaaS pilot study on the interrelation between MaaS and private car
24	India's shift from mass transit to MaaS transit: Insights from Kochi	(Singh, 2020b)	India	Case reports	Highlights MaaS ability to augment mobility governance and service provision in India
25	Exploring motivational mechanisms behind the intention to adopt mobility as a service (MaaS): Insights from Germany	(Schikofsky et al., 2020)	Germany	Empirical	Explores main motivational mechanisms behind the intention to adopt MaaS

26	Prototype business models for Mobility-as-a-Service	(Polydoropoulou et al., 2020)	Greece	Case reports	Identifies enablers and barriers for MaaS business models in 3 European cities
27	Mobility as a service in community transport in Australia: Can it provide a sustainable future?	(Mulley et al., 2020)	Australia	Empirical	Investigates the mobility services that users are be willing to pay for in the new era of person-centered funding
28	Organizing integrated services in mobility-as-a-service systems: Principles of alliance formation applied to a MaaS-pilot in the Netherlands	(Meurs et al., 2020)	the Netherlands	Conceptual	Presents different suppliers of transport services and factors that may limit the formation of the MaaS
29	Reprint of: The importance of user perspective in the evolution of MaaS	(Lyons et al., 2020)	UK	Theorical	Argues that MaaS is an evolutionary continuation in terms of transport integration
30	People's current mobility costs and willingness to pay for Mobility as a Service offerings	(Liljamo et al., 2020)	Finland	Empirical	Assesses the willing to adopt MaaS packages based on a survey
31	Development and implementation of Mobility-as-a-Service – A qualitative study of barriers and enabling factors	(Karlsson et al., 2020)	Sweden	Case reports	Describes and analyzes the enablers and barriers to the development of MaaS based on a case study
32	Public preferences for mobility as a service: Insights from stated preference surveys	(Ho et al., 2020)	Australia	Theorical	Analyzes the barriers to a widespread adoption of MaaS and the potential impacts on PT use.
33	MaaS surveillance: Privacy considerations in mobility as a service	(Cottrill, 2020)	UK	Conceptual	Predicates MaaS services upon the sharing of personal travel information
34	Children, Young people, and Mobility as a Service: Opportunities and barriers for future mobility	(Casadó et al., 2020)	Spain	Empirical	Presents barriers to acceptance and adoption of MaaS and the underpinning transport services reservations
35	Bundling, pricing schemes and extra features preferences for mobility as a service: Sequential portfolio choice experiment	(Caiati et al., 2020)	The Netherlands	Conceptual	Estimates the latent demand for MaaS using a choice model based on a stated preference survey
36	Assessing the welfare impacts of Shared Mobility and Mobility as a Service (MaaS)	(Becker et al., 2020)	Switzerland	Case reports	Presents efficient alternatives to PT to reduce transport-related energy consumption
37	A MaaS platform architecture supporting data sovereignty in sustainability assessment of manufacturing systems	(Landolfi et al., 2019)	Switzerland	Theorical	Describes the architecture behind a platform in the Manufacturing as a Service (MaaS) domain
38	Exploring the possibility of MaaS service in Thailand, implications from the existing conditions and experts' opinions	(Narupiti, 2019)	Thailand	Conceptual	Analyzes the literature and a collection of present transport setting for the identification of the suitable MaaS provider
39	The Ws of MaaS: Understanding mobility as a service from literature review	(Arias & C., 2020)	Spain	Conceptual	Defines the MaaS ecosystem and key stakeholders and the modalities of cooperation.
40	MaaS users: Who they are and how much they are willing-to-pay	(Tsouros et al., 2021)	Greece	Empirical	Explores models & users' preferences and choices based on an online survey

41	Comparison of the willingness to adopt MaaS in Madrid (Spain) and Randstad (The Netherlands) metropolitan areas	(Lopez-Carreiro et al., 2021)	Spain	Empirical	Assesses the acceptance and willingness to adopt MaaS based on gender, age, education level, and occupation influence
42	Tourists' preference on the combination of travel modes under Mobility-as-a-Service environment	(E.-J. Kim et al., 2021)	Korea	Empirical	Explores tourists' preference in the context of tour-based mode choice
43	Mobility as a service and private car use: Evidence from the Sydney MaaS trial	(Hensher et al., 2021)	Australia	Empirical	Investigates the potential for changes in monthly car use following a MaaS program
44	Technological advances relevant to transport – understanding what drives them	(Cohen & Jones, 2020)	UK	Conceptual	Examines four areas of technological advance relevant to transport including MaaS
45	Mobility-As-A-Service: Concepts and Theoretical Approach	(šulskytė, 2021)	Lithuania	Theorical	Highlights the MaaS barriers such as deficiency of cooperation, digital illiteracy, and unfavorable government policies
46	Application of crowdsourced data to infer user satisfaction with Mobility as a Service (MaaS)	(Aman & Smith-Colin, 2022)	USA	Empirical	Obtains the features of the MaaS platforms that influence user satisfaction levels across gender
47	Data mining technologies for Mobility-as-a-Service (MaaS)	(Shang et al., 2022)	China	Theorical	Explains how big data technology can be enabled for MaaS
48	Enhancing traveler experience in integrated mobility services via big data social data analytics		Italy	Conceptual	Proposes a data-driven approach to boost the tourist experience in integrated mobility services
49	Resilience analysis and design for mobility-as-a-service based on enterprise architecture modeling	(Zhou et al., 2023)	Japan	Theorical	Proposes speculative reports on MaaS service-level reliability concerns
50	Mobility as a Service Inclusion Index (MaaSINI): Evaluation of inclusivity in MaaS systems and policy recommendations	(Dadashzadeh et al., 2022)	UK	Conceptual	Discusses the supply and demand sides of MaaS systems considering the Vulnerable Social Groups' demands.
51	Barriers to the adoption of the mobility-as-a-service concept: The case of Istanbul, a large emerging metropolis	(Kayikci & Kabadurmus, 2022)	Turkey	Case reports	Examines the major obstacles to the effective deployment of MaaS in the context of developing countries.
52	Mobility-as-a-service: insights to policymakers and prospective MaaS operators	(Pagoni et al., 2022)	Greece	Empirical	Carries out a thorough analysis of the current European rules and policy framework
53	MaaS to pull us out of a car-centric orbit: Principles for sustainable Mobility-as-a-Service in the context of unsustainable car dependency	(Pritchard, 2022)	UK	Conceptual	Presents the economic, environmental, and social issues with car dependency and the MaaS principles for sustainability
54	The influence of latent lifestyle on acceptance of Mobility-as-a-Service (MaaS): A hierarchical latent variable and latent class approach	(S. Kim & Rasouli, 2022)	The Netherlands	Empirical	Investigates how people's lifestyles are associated with MaaS acceptance

55	Can MaaS change users' travel behavior to deliver commercial and societal outcomes?		Australia	Conceptual	Quantify the net impact of MaaS and verify its potential to achieve societal goals with a focus on the commercial outcomes.
56	Towards sustainable transport in developing countries: Preliminary findings on the demand for MaaS in Metro Manila	(Hasselwander et al., 2022)	Portugal	Case reports	Investigates the main adoption reasons and the way it impacts the use of PT.
57	The distributed ownership of on-demand mobility service	(Gong et al., 2022)	Australia	Theorical	Demonstration of the potential use of blockchain in the MaaS marketplace.
58	Predicting Mobility as a Service (MaaS) use for different trip categories: An ANN analysis		Australia	Conceptual	Production of predictive models for MaaS use by applying ANN analysis.
59	Consumer preferences for operator collaboration in intra- and intercity transport ecosystems: Institutionalizing platforms to facilitate MaaS 2.0	(Bushell et al., 2022)	Australia	Theorical	Proposes a method of institutional integration MaaS 2.0 to create a better value
60	The commercial viability of MaaS: what is in it for existing transport operators, and why should governments intervene?	(AkshayVij, 2022)	Australia	Conceptual	Examines the ability to persuade operators to join MaaS platform with the substitutive services integration
61	Does MaaS address the challenges of multi-modal mothers? User perspectives from Brussels, Belgium	(E. Cooper & Vanoutrive, 2022)	Belgium	Case reports	Focuses on Brussels where MaaS is promoted as a flexible, efficient mode but walking is already the dominant mode
62	Listening to users' personal privacy concerns. The implication of trust and privacy concerns on the user's adoption of a MaaS-pilot	(Huang, 2022b)	Norway	Conceptual	Aims to contribute to earlier literature on privacy concerns by shedding light on the MaaS service dimensions
63	Exploring relevant factors behind a MaaS scheme	(Macedo et al., 2022)	Portugal	Theorical	Demonstrates that there is no agreed-upon definition, nor universal best way to evaluate and compare schemes
64	Understanding the potential of MaaS – A European survey on attitudes	(Matowicki et al., 2022)	Czech	Empirical	Provides insights on the characteristics and attitudes of potential MaaS users based on an online survey
65	Transport Authorities and Innovation: Understanding Barriers for MaaS Implementation in the Global South	(Hasselwander & Bigotte, 2022)	Portugal	Conceptual	Sheds light on barriers that transport authorities face based on the technology, organization, and environment framework
66	Multidimensional Indicator of MaaS systems Performance	(Bandeira et al., 2022)	Portugal	Theorical	Propose a multidimensional system based on three dimensions (coverage, functionality, and sustainability)
67	Unpacking the complexities of MaaS business models – A relational approach		Sweden	Conceptual	Argues that the ecosystem approach to the MaaS business models analysis can capture its complexity

68	MaaS system visualization	(Yang et al., 2022)	Japan	Theorical	Reviews existing visualization technologies of the current transportation system, including MaaS
69	Mobility as a service: exploring the opportunity for mobility as a service in the UK	(Datson, 2016)	UK	Conceptual	Discusses the two core strengths to MaaS business model: Servitization and data sharing
70	In the City-as-a-Platform: The Case of Mobility-as-a-Service	(Pizzi, 2021)	Italy	Theorical	Show why and how MaaS is defined through the lenses of technology, philosophy, and mobility

Appendix B -Web Scraping

The technique used in this research to extract data from websites involves retrieving HTML content from web pages and then parsing and extracting specific information from that content. Python offers several libraries for web scraping, with Beautiful Soup and Requests being commonly used for this purpose. Here is the Python script, followed by a brief explanation:

```python
# Import necessary libraries
import requests            # For sending HTTP requests
from bs4 import BeautifulSoup  # For parsing HTML content

# Define the URL of the MaaS company's webpage
url = 'https://maascompany.com'

# Send an HTTP GET request to the specified URL
response = requests.get(url)

# Parse the HTML content of the page using BeautifulSoup
soup = BeautifulSoup(response.text, 'html.parser')

# Find the HTML element (usually a <h1>) containing the company name
company_name_element = soup.find('h1', class_='company-name')

# Extract the text content of the company name element
company_name = company_name_element.text.strip() if company_name_element else 'N/A'

# Find the HTML element (usually a <div>) containing the integration level
integration_level_element = soup.find('div', class_='integration-level')

# Extract the text content of the integration level element
integration_level = integration_level_element.text.strip() if integration_level_element else
'N/A'

# Print the extracted company name and integration level
print (f'Company Name: {company_name}')
print (f'Integration Level: {integration_level}')
```

This script does the following:

- Imports the necessary libraries (requests for sending HTTP requests and BeautifulSoup for parsing HTML content).
- Defines the URL of the MaaS company's webpage to scrape.
- Sends an HTTP GET request to the specified URL to retrieve the webpage's HTML content.
- Parses the HTML content using BeautifulSoup for easier manipulation.
- Finds the HTML element (usually a <h1>) containing the company name on the webpage.
- Extracts the text content of the company name element and stores it in the company_name variable. If no element is found, it assigns 'N/A' to company_name.

- Finds the HTML element (usually a <div>) containing the integration level and the other elements.
- Extracts the text content of the integration level element and stores it in the integration_level variable. If no element is found, it assigns 'N/A' to integration_level. The same procedure applies to the other elements.
- Finally, it prints the extracted company name and the other results.

To use the script, the URL 'https://maascompany.com' must be replaced with the actual URL of the MaaS company to scrape.

For this research, the web scraping was conducted in compliance with the website's terms of service and legal regulations. Some websites have restrictions on data scraping, so it was essential to review and respect these guidelines. Additionally, it considered the ethical implications and potential impact on the website's performance when scraping data.

Appendix C-MaaS organization database 01

MaaS Company	Operator (Public/Private)	Status	Integration level	Number	Weblink
	Private RACV (Private)	2019-present	1	6	arevo.com.au
	Free2move (Public)	2016-present	1	5	free2move.com
	Intel (Private)	2012-present	1	6	moovitapp.com
	Road transport authority (Public)	2017-present	1	4	rta.ae
	Verkehr Mobilität und Zukunft(Private)	2019-present	2	6	vmzberlin.com
	Citen (Private)	2020-present	2	6	citenapp.com
	CityMapper (Private)	2011-present	2	7	citymapper.com
	DerbyGo (Private)	2021-2023	2	5	derby-go.uk
	Keolis & Dijon (Public)	2012-present	2	4	divia.fr
	Odakuyu electric(Private)	2019-present	2	5	odakyu.jp
	fromAtoB (Private)	2008-2020	2	7	fromatob.de
	Arriva (Private)	2021-present	2	7	arriva.co.uk
	HITRANS (Public)	2021-present	2	9	hitrans.org.uk
	HtoH (Private)	2020-present	2	4	htoh.io
	Gojek (Private)	2010-present	2	3	gojek.com
	Hacon (Private)	2019-present	2	8	hacon.de
	HVV (Public)	2020-present	2	4	hvv.de
	Imbric (Private)	2011-present	2	4	imbric.com
	KINTO Go (Public)	2019-present	2	7	kinto-mobility.eu
	Mobilflow (Private)	2017-present	2	7	mobiflow.be
	STIB (Public)	2020-present	2	7	stib-mivb.be
	Mycecero (Public)	2015-present	2	6	mycicero.it
	Uberider (Private)	2018-present	2	7	pick.ubirider.com
	River City Transport authority (Public)	2019-present	2	6	ridetarc.org
	istra (Public)	2007-pressent	2	4	uestra.de
	Wiener (Public)	2018-present	2	6	wienerlinien.at
	Wegfinder OBB (Public)	2015-present	2	5	wegfinder.at
	Yuway (Private)	2019-present	2	5	yuwway.com
	Ridecell (Private)	2018-present	2	7	ridecell.com
	Zoox (Private)	2014-present	2	5	zoox.com
	Via-ID (Public)	2013-present	3	6	via-id
	Gayio (Private)	2008-present	3	6	gaiyo.com
	GVH (public)	2004-present	3	6	gvh.de
	Grab (Public)	2021-present	3	6	grab.com
	Mobility inside (Private)	2020-present	3	3	mobility-inside.de
	Modalizy (Private)	2017-present	3	5	modalizy.be
	Moovizy Saint-Etienne (Public)	2016-present	3	9	reseau-stas.fr
	Quicko (Private)	2018-present	3	8	quicko.com
	NCF (Public)	2019-present	3	4	sncf.com
	Travelspirit (Private)	2015-present	3	8	www.travelspirit.io
	Cityway (Private)	2017-present	4	7	cityway.io
	Here (Private)	2010-present	4		here.com
	BVG-Berlin (Public)	2019-present	4	9	jelbi.de
	MaaStran	2017-present	4	8	www.maastran.co.uk
	BMW-Daimler AG (Private)	2015-present	4	4	your-now
	MOTC (Public)	2020-pressent	4	8	motc.gov.tw
	MaaS Global (Private)	2017-present	4	7	whimapp.com
	umuv SBB (Private)	2020-present	4	7	yumuv.ch
	Velocia	2014-present	4	9	velocia.io
	MobFi (Private)	2021-present	4	8	mobifi.io

Appendix D -MaaS corporations database 02

Company Name	Type	Website	Year of Creation	Integration level	Count of Mobility Modes
Airlift	Private	airliftglobal.co/	2019	High	3
Autonomy	Private	autonomy.tech/	2015	High	6
Beam	Private	ridebeam.com/	2018	Medium	3
Beat	Private	thebeat.co/	2011	High	4
Beryl	Private	beryl.cc/	2012	Low	3
Bird	Private	www.bird.co/	2017	Low	3
BlaBlaCar	Private	www.blablacar.com/	2016	Low	3
Blink	Private	blinkmobility.com/	2020	High	3
Blu Smart	Private	blu-smart.com/	2018	High	5
BlueSG	Private	www.bluesg.com.sg/	2017	Medium	3
Bolt	Private	bolt.eu/	2013	High	4
Bounce	Private	www.bounceshare.com/	2014	Low	3
Bridj	Private	www.bridj.com/	2012	High	3
BusUp	Private	www.busup.com/	2015	High	4
BVG-Berlin	Private	jelbi.de	2019	High	9
Cabify	Private	cabify.com/	2011	High	3
Car2go	Private	www.car2go.com/	2008	High	3
Careem	Private	www.careem.com/	2012	High	6
Caroo Mobility	Private	caroomobility.com/	2019	Medium	3
Catch a Car	Private	www.catch-a-car.ch/	2014	High	3
ChargePoint	Private	www.chargepoint.com/	2007	High	3
Citen	Private	citenapp.com	2020	Medium	6
Citylift	Private	citylift.io/	2021	Low	3
Citymapper	Private	citymapper.com/	2011	High	6
Cityscoot	Private	www.cityscoot.eu/	2014	Low	3
Cityway	Private	cityway.io	2017	High	7
Co-wheels	Private	www.co-wheels.org.uk/	2014	Medium	4
Commutifi	Private	www.commutifi.com/	2015	High	7
Cooltra	Private	www.cooltra.com/en/	2016	High	3
COUP	Private	www.joincoup.com/	2016	High	3
Curb Mobility	Private	gocurb.com/	2007	Medium	3
Didi Chuxing	Private	www.didiglobal.com/	2012	High	7
DiDi Mobility Japan	Private	didi-mobility.jp/	2018	High	5
Donkey Republic	Private	www.donkey.bike/	2015	Low	3
Dott	Private	ridedott.com/	2018	Low	3
DriveNow	Private	www.drive-now.com/	2011	High	3
EasyMile	Private	www.easymile.com/	2014	High	3
elops	Private	elops.city/	2019	High	4

Felyx	Private	felyx.com/	2017	Low	3
Flinkster	Private	www.flinkster.de/	2012	High	3
Free2Move	Private	www.free2move.com/	2016	High	6
G7	Private	www.g7.fr/	2017	High	6
Gayio	Private	gaiyo.com	2008	High	6
Getaround	Private	www.getaround.com/	2009	Low	3
Gett	Private	gett.com/	2010	High	4
GIG Car Share	Private	gigcarshare.com/	2018	Low	3
GoCar Malaysia	Private	www.gocar.my/	2015	High	3
GoGet	Private	www.goget.my/	2010	High	3
Goggo Network	Private	goggo.network/	2017	High	7
Gogoro	Private	www.gogoro.com/	2011	Low	3
GoMetro	Private	gometroapp.com/	2012	Medium	4
Grab	Private	www.grab.com/	2012	High	9
Gruv	Private	gruv.app/	2019	Medium	4
Hacon	Private	hacon.de	2019	Medium	8
Hailo	Private	hailoapp.com/	2011	High	6
Heetch	Private	heetch.com/en/	2013	High	7
Helbiz	Private	www.helbiz.com/	2018	Medium	3
HITRANS	Private	hitrans.org.uk	2021	Medium	9
HOPR	Private	hopr.com/	2019	High	3
Hopr	Private	hopr.com/	2018	High	3
iCabbi	Private	www.icabbi.com/	2009	High	3
Invers	Private	invers.com/	2007	High	5
JUMP	Private	jump.com/	2010	Low	3
Kapten	Private	www.kapten.com/en/	2012	High	5
Karhoo	Private	www.karhoo.com/	2016	High	6
Kater	Private	ridekater.com/	2018	High	7
Keolis	Private	www.keolis.com/	2012	High	5
Keolis & Dijon	Private	divia.fr	2012	Medium	4
Kinto	Private	www.kinto.com/	2019	High	3
Kyyti Group	Private	kyyti.com/	2016	High	9
Liftshare	Private	liftshare.com/	2018	Low	3
Lime	Private	www.li.me/	2017	High	3
Locomute	Private	www.locomute.in/	2019	High	3
Lyft	Private	www.lyft.com/	2012	High	7
Lynk & Co	Private	www.lynkco.com/	2016	High	3
MaaS Global	Private	maas.global/	2015	High	6
Masabi	Private	www.masabi.com/	2008	High	4
Micromobility	Private	www.micromobility.io/	2018	High	3
Migo	Private	gomigo.com/	2016	High	5
Mobike	Private	mobike.com/	2015	Low	3

Mobilflow	Private	mobiflow.be	2017	Medium	7
Mobility ADO	Private	www.ado.com.mx/movilidad	2020	High	3
Mobility inside	Private	mobility-inside.de	2020	High	3
Mobility Mixx	Private	www.mobilitymixx.nl/	2012	High	4
Mobilize	Private	www.mobilize.com/	2020	High	4
Mobilleo	Private	www.mobilleo.com/	2015	High	8
Modalizy	Private	modalizy.be	2017	High	5
Modo	Private	modo.coop/	2017	High	5
Moia	Private	www.moia.io/	2016	High	3
Moja Ride	Private	www.mojaride.co.ke/	2018	Low	3
Moovel	Private	www.moovel.com/	2013	High	4
Moovit	Private	moovitapp.com/	2012	High	3
Mycecero	Private	mycicero.it	2015	Medium	6
mytaxi	Private	www.mytaxi.com/	2009	High	2
Neuron Mobility	Private	www.neuron.sg/	2016	High	6
Nextbike	Private	www.nextbike.net/	2014	Low	3
OBike	Private	www.obike.com/	2017	Low	3
Ofo	Private	www.ofo.com/	2014	Low	3
Ohayo	Private	www.ohayomobility.com/	2017	High	5
OjO Electric	Private	www.ojoelectric.com/	2015	High	4
Ola	Private	www.olacabs.com/	2010	High	6
Onzo	Private	onzo.co.nz/	2014	Low	3
Oply	Private	www.oply.com/	2018	Medium	2
Optibus	Private	www.optibus.com/	2014	High	4
Pogo	Private	www.pogocarshare.com/	2017	High	3
Pony.ai	Private	www.pony.ai/	2016	High	3
Poppy	Private	poppy.be/	2018	Medium	4
Qixxit	Private	www.qixxit.de/	2012	High	6
Quicko	Private	quicko.com	2018	Low	8
RACV	Private	arevo.com.au	2019	Low	6
Rapido	Private	rapido.bike/	2015	High	3
Razor	Private	www.razor.com/share/	2010	Low	3
Rentrip	Private	www.rentrip.in/	2017	High	3
Ridecell	Private	ridecell.com/	2009	High	4
Routematch	Private	www.routematch.com/	2010	High	3
Ryde	Private	www.rydesharing.com/	2014	High	3
Rydies	Private	rydies.com/	2018	Low	3
ShareNow	Private	www.share-now.com/	2019	High	6
Sherpa	Private	sherpa-mobilite.fr/	2017	High	2
Shotl	Private	shotl.com/	2016	High	6
Shuttl	Private	www.ridewithshuttl.com/	2015	High	3
Sixt Share	Private	www.sixt.com/sixt-share/	2018	High	3

SkedGo	Private	skedgo.com/	2010	High	6
Skip	Private	www.skipscooters.com/	2017	Low	3
Skoot Mobility	Private	www.skootride.com/	2018	Low	3
Smoov	Private	smoovapp.eu/	2008	High	3
Smove	Private	smove.sg/	2013	High	7
Spin	Private	www.spin.app/	2016	Medium	3
Splyt	Private	www.splyt.com/	2013	High	3
STIB	Private	stib-mivb.be	2020	Medium	7
StreetCrowd	Private	streetcrowd.com/	2015	High	3
Svipe	Private	www.svipe.com/	2017	High	3
Swapfiets	Private	swapfiets.nl/en	2015	Low	3
Swvl	Private	swvl.com/	2017	High	2
TaxiTender	Private	www.taxitender.com/	2013	Medium	3
TIER Mobility	Private	www.tier.app/	2018	Low	3
Trafi	Private	www.trafi.com/	2013	High	6
Transit	Private	transitapp.com/	2011	High	4
Transit Systems	Private	www.transitsystems.com/	2012	High	7
Trive	Private	www.trive.me/	2017	Medium	3
Turo	Private	turo.com/	2010	Low	3
Ubeeqo	Private	www.ubeeqo.com/en-gb	2008	High	6
UbiGo	Private	www.ubigo.se/	2013	High	6
Udrive	Private	udrive.ae/	2017	Low	3
UGo	Private	ugo.city/	2019	High	3
Unu	Private	unumotors.com/de/	2013	Low	3
Urbee	Private	urbee.nl/	2016	Low	3
Urbo	Private	www.urbo.com/	2017	High	5
Veo	Private	veoride.com/	2017	High	3
VIA	Private	ridewithvia.com/	2012	High	7
Vianova	Private	vianova.io/	2018	High	3
VOI Technology	Private	www.voiscooters.com/	2018	Low	3
Voiager Mobility	Private	www.voiagermobility.com/	2017	Low	3
Wegfinder OBB	Private	wegfinder.at	2015	Medium	5
WeMo Sharing	Private	wemo-app.com/	2019	Medium	3
WeShare	Private	www.volkswagen-we.com/en/weshare.html	2019	High	6
Wheels	Private	www.getwheelsapp.com/	2018	Medium	3
Whim	Private	whimapp.com/	2016	High	8
Whistle	Private	whistle.com/	2021	Medium	3
WhizzGo	Private	www.whizzgo.co.uk/	2013	High	3
Wind Mobility	Private	www.wind.co/	2017	Low	3
Wingo	Private	wingo.car/	2018	Medium	3
Wolt	Private	wolt.com/	2014	Medium	3

Wunder Mobility	Private	www.wundermobility.com/	2014	High	6
Youon	Private	youonbike.com/	2015	High	3
Yourdrive	Private	yourdrive.co.nz/	2015	Low	3
Yumuv SBB	Private	yumuv.ch	2020	High	7
Zify	Private	zify.eu/	2013	Low	3
Zipcar	Private	www.zipcar.com/	2010	Medium	3
ZITY	Private	www.zitycar.es/	2017	High	3
Arriva	Public	www.arriva.co.uk/	2021	Medium	7
Beeline Singapore	Public	www.beeline.sg/	2015	High	3
Bixi	Public	bixi.com/	2009	Low	3
DerbyGo	Public	derby-go.uk	2021	Medium	5
Divvy Bikes	Public	www.divvybikes.com/	2013	Low	3
Edenred	Public	www.edenred.com/	2016	High	3
Gojek	Public	gojek.com	2010	Medium	3
GreenMobility	Public	greenmobility.com/	2016	High	3
GVH	Public	gvh.de	2014	High	6
HSL	Public	www.hsl.fi/en	2010	High	7
HVV	Public	hvv.de	2020	Medium	4
Imbric	Public	imbric.com	2011	Medium	4
Intel	Public	moovitapp.com	2012	Low	6
Jelbi	Public	www.jelbi.de/	2019	High	3
Meep	Public	www.meep.me/	2018	High	4
Moovizy	Public	reseau-stas.fr	2016	Medium	9
MOTC	Public	motc.gov.tw	2020	High	8
MTR Express	Public	www.mtrexpress.se/	2015	High	3
Odakuyu elektric	Public	odakyu.jp	2019	Medium	5
Road transport authority	Public	rta.ae	2017	Low	4
SNCF	Public	sncf.com	2019	High	4
Sumitomo	Public	www.sumitomocorp.com/en/jp/business/	2019	High	6
Transport authority of River City	Public	ridetarc.org	2019	Medium	6
Uber	Public	www.uber.com/	2009	High	9
Veligo	Public	www.veligo.fr/	2019	High	6
Verkehr, Mobilität und Zukunft	Public	vmzberlin.com	2019	Low	6
Via-ID	Public	via-id	2013	High	6
Wiener	Public	wienerlinien.at	2018	Medium	6
Your-now	Public	your-now	2015	Medium	4
Yuway	Public	yuwway.com	2019	Medium	5

Appendix E -MaaS ecosystem components and data

1. MaaS revenue category

MaaS Revenue Category	Structured Data	Unstructured Data
a) Cost Structure	- Investment and operating expenses data	- None
b) Revenue Streams	- Pay-as-you-go and membership fare data	- Transaction fees data
	- None	- Royalties data for advertisements and marketing
c) Customer Segments	- Consumer preferences and attributes data	- Classification of consumers
	- Mobility and modality preferences data	- None
	- Frequency of travel data	- None
	- Spatial dimension data	- None
d) Customer Relationships	- Customer feedback and ratings data	- Social media interactions data
	- Personalized customer support data	- None
e) Customer Channels	- Sales and customer service data	- Media (newspapers, magazines) data
	- Digital platforms (websites, social media, apps)	- None
f) Main Resources	- IT infrastructure components data	- Data sources (user data, climate, events)
	- Vehicles and transportation infrastructure data	- None
g) Main Activities	- Categorized key activities data	- Internal and external core actions data
	- Partner integration level data	- None
h) Main Partners	- Mobility and non-mobility service providers data	- IT service providers data
	- Regulatory agencies data	- Financial conciliators data
	- Legal entities and payment operators' data	- None

2. MaaS value proposition category

Value Proposition Category	Structured Data	Unstructured Data
a) Value Elements	- Features and attributes data	- Customer reviews and testimonials
	- Performance metrics data	- None
	- Customization options data	- None
	- Accessibility features data	- None
b) Problem Solving	- Identification of pain points data	- Customer feedback and complaints data

	- Solutions offered data	- None
	- Improvements over existing options data	- None
c) Innovation	- Unique selling points data	- Market trend analysis data
	- Technological differentiators data	- None
	- Creative solutions data	- None
d) Customer Gains	- Time and cost savings data	- None
	- Convenience and accessibility gains data	- None
	- Quality of life improvements data	- None
e) Customer Pains	- Inconveniences addressed data	- Customer challenges and frustrations data
	- Negative impacts mitigated data	- None
	- Previous negative experiences data	- None
f) Emotional Jobs	- Customer emotions targeted data	- User sentiment analysis data
	- Psychological benefits data	- None
	- Social status enhancement data	- None
g) Social Jobs	- Community engagement data	- None
	- Environmental impact data	- None
	- Societal contribution data	- None
h) Supporting Evidence	- Case studies and success stories data	- None
	- Comparative data (vs. competitors)	- None
	- Research and expert endorsements data	- None

3. MaaS customer category

MaaS Customer Category	Structured Data	Unstructured Data
a) Customer Profile	- Demographic data	- Customer surveys and feedback
	- Geographic data	- User-generated content (blogs, forums)
	- Socioeconomic data	- None
b) Needs and wishes	- Travel patterns data	- Customer comments and opinions
	- Mobility preferences data	- None
	- Service expectations data	- None
c) Pain Points	- Inconvenient routes/data	- Negative customer experiences data
	- Unreliable services data	- None
	- High costs data	- None
d) Gains	- Time and cost savings data	- None
	- Seamless travel experience data	- None
	- Convenience gains data	- None
e) Emotional Drivers	- Desired travel experiences data	- User sentiment analysis data
	- Lifestyle alignment data	- None
	- Sense of community data	- None
f) Social Drivers	- Environmental awareness data	- None
	- Social responsibility data	- None
	- Peer influence data	- None

g) Decision Making	- Value for money data	- Customer reviews and recommendations
	- Service reliability data	- Online discussions and opinions
	- User reviews and ratings data	- None
h) Communication	- Customer support interactions data	- Social media interactions data
	- Feedback and complaint data	- None
	- User-generated content (reviews)	- None

4. MaaS infrastructure category

MaaS Infrastructure Category	**Structured Data**	**Unstructured Data**
a) Physical Infrastructure	- Transportation network data	- None
	- Stations and stops data	- None
	- Vehicle fleet data	- None
b) Digital Infrastructure	- Mobile app data	- User reviews and feedback
	- Website data	- None
	- Backend systems data	- None
c) Payment Systems	- Payment methods data	- User payment complaints and feedback
	- Fare structure data	- None
	- Loyalty programs data	- None
d) Data Sources	- GPS and location data	- User-generated data (check-ins, reviews)
	- Traffic and congestion data	- None
	- Weather data	- None
e) Data Management	- Data storage and processing data	- None
	- Data security measures data	- None
	- Data privacy compliance data	- None
f) Interoperability	- Integration protocols and APIs data	- None
	- Data sharing agreements data	- None
	- Cross-platform compatibility data	- None
g) Maintenance	- Maintenance schedules and records data	- None
	- Vehicle inspection data	- User complaints and feedback
	- Infrastructure repairs data	- None
h) Expansion and Upgrades	- Expansion plans and proposals data	- None
	- Technology upgrades data	- User suggestions and recommendations
	- Market research for expansion data	- None

Appendix F-Data pre-processing code - Python package

Code 01

```
import spacy
import PyPDF2

# spacy english model (large)
nlp = spacy.load('en_core_web_lg')

# method for reading a pdf file
def readPdfFile(filename, folder_name):

# storing path of PDF-Documents folder
data_path = str(os.getcwd()) + "\\" + folder_name

file = open(data_path + "\\" + filename, mode="rb")

# looping through pdf pages and storing data
pdf_reader = PyPDF2.PdfFileReader(file)
num_pages = pdf_reader.numPages

# traverse through each page and store data as an
element in list
text = []
for pages in range(0, num_pages):
current_page = pdf_reader.getPage(pages)
text.append(current_page.extractText().replace("\n","").l
ower())

# # remove \n from list
# text = [t.replace("\n", "").lower() for t in text]

# store content of 1-last page in a seperate list
rest_pages = []
for t in text[1:]:
rest_pages.append(t[115:])

# store 0th page content separately
first_page = [text[0][850:]]

# storing the 0th and 1-last page content after cleaning i
text
text = first_page + rest_pages

# creating a single string containing full text
full_text = "".join(text)

return full_text


# customer sentence segmenter for creating spacy
document object
def setCustomBoundaries(doc):
# traversing through tokens in document object
for token in doc[:-1]:
if token.text == ';':
doc[token.i + 1].is_sent_start = True
if token.text == ".":
doc[token.i + 1].is_sent_start = False
return doc


# create spacy document object from pdf text
def getSpacyDocument(pdf_text, nlp):
main_doc = nlp(pdf_text) # create spacy document objec


return main_doc

# adding setCusotmeBoundaries to the pipeline
nlp.add_pipe(setCustomBoundaries, before='parser')
```

Code 02

```
# convert keywords to vector
def createKeywordsVectors(keyword, nlp):
doc = nlp(keyword) # convert to document object

return doc.vector


# method to find cosine similarity
def cosineSimilarity(vect1, vect2):
# return cosine distance
return 1 - spatial.distance.cosine(vect1, vect2)


# method to find similar words
def getSimilarWords(keyword, nlp):
similarity_list = []

keyword_vector = createKeywordsVectors(keyword,
nlp)

for tokens in nlp.vocab:
if (tokens.has_vector):
if (tokens.is_lower):
if (tokens.is_alpha):
similarity_list.append((tokens,
cosineSimilarity(keyword_vector, tokens.vector)))

similarity_list = sorted(similarity_list, key=lambda
item: -item[1])
similarity_list = similarity_list[:30]

top_similar_words = [item[0].text for item in
similarity_list]

top_similar_words = top_similar_words[:3]
top_similar_words.append(keyword)

for token in nlp(keyword):
top_similar_words.insert(0, token.lemma_)

for words in top_similar_words:
if words.endswith("s"):
top_similar_words.append(words[0:len(words)-1])

top_similar_words = list(set(top_similar_words))

top_similar_words = [words for words in
top_similar_words if enchant_dict.check(words) ==
True]

return ", ".join(top_similar_words)


keywords = ['label', 'package']
similar_keywords = getSimilarWords(keywords, nlp)
```

Appendix G -Distribution of Use cases from MaaS data across urban planning domains

Type of MaaS Data	Domain	Use Case in City Planning
Parking Data	Collaboration	Event Management
Event Data		Event Management
Tourism Data		Tourism Planning
Event Data		Multi-Modal Transportation Integration
Public Transit Data		Peak time traffic Management
Tourism Data		Tourist Flow Management
Social Equity Data		Social Equity
Urban Development Data		Open Spaces Design
Land Use Data		Land Use Planning
Public Transit Data		Inner-city logistics and Transportation
Economic Data		Tourism Impact Assessment
Social Equity Data		Elderly and Disabled Mobility
Public Health Data		Social Services
Social Equity Data		Social Equity
Air Quality Data		Tourism Development
Tourism Data		Tourism Planning
Environmental Data		Tourism Marketing
Public Transit Data		Airports Integration
Event Data		Citywide Events Calendar
Public Health Data		Public Health Initiatives
Economic Data		Crisis Response Coordination
Event Data		Emergency Evacuation Planning
Pedestrian and Cyclist Data		Accessibility Assessment
Tourism Data		Crisis Response Coordination
Social Equity Data		Policy Measures with Events
Environmental Data		Electric Vehicle Incentives
Public Transit Data		Waterfront Transportation Integration
Land Use Data		Waterfront Transportation Planning
Environmental Data	Innovation	Environmental Impact Assessment
Environmental Impact Data		Enhancing Sustainable Urban Mobility
Public Transit Data		Micro-Mobility Planning
Parking Data		Smart Street Lighting
Environmental Data		Street Lighting optimization
Traffic Data		Traffic Education Programs
Infrastructure Data		Electric Bus Routes
Parking Data		Smart Transit Hubs

Event Data		Smart Transit Development
Environmental Impact Data		Social Behavior Analysis
Pedestrian and Cyclist Data		Social Interaction Assessment
Urban Development Data		Examination of Societal Actions
Infrastructure Data		Infrastructure Impact on Social Behavior
Social Equity Data		Infrastructure Planning and Social Behavior
Environmental Data		Environmental Impact on Social Behavior
Pedestrian and Cyclist Data		Sustainable Development Planning
Urban Development Data		Urban Development
Traffic Data	Resource Management	Traffic Flow Optimization
Infrastructure Data		Infrastructure Maintenance
Public Transit Data		Public Transit Planning
Traffic Data		Congestion Pricing
Public Transit Data		School Transportation Planning
Environmental Data		Freight and Logistics Optimization
Public Health Data		Healthcare Access
Parking Data		Parking Management
Air Quality Data		Air Quality Monitoring
Public Health Data		Emergency Medical Services
Infrastructure Data		Infrastructure Maintenance
Public Transit Data		Urban Freight Delivery Zones Planning
Public Transit Data		Rural Mobility Services
Land Use Data		Rural Mobility Integration
Social Equity Data		Sustainable Infrastructure Planning
Environmental Data		Eco-friendly Infrastructure Development
Environmental Impact Data	Sustainability	Climate Change Mitigation
Public Transit Data		Pedestrian Walkability
Air Quality Data		Green Space Conservation
Environmental Impact Data		Green roof Promotion
Environmental Data		Parks Conservation
Pedestrian and Cyclist Data		Pedestrian Safety Campaigns
Air Quality Data		Green Spaces Planning
Pedestrian and Cyclist Data		Green Spaces Optimization
Land Use Data		Green Spaces Development
Environmental Data		Parks Planning
Pedestrian and Cyclist Data		Cycling Infrastructure
Pedestrian and Cyclist Data		Pedestrian Safety
Economic Data	Governance	Parking Enforcement
Event Data		Ensuring public safety during festivals and gatherings.
Pedestrian and Cyclist Data		Promoting active transportation for health benefits.

Tourism Data		Enhancing tourist experiences
Social Equity Data		Identifying areas with limited access
Environmental Data		Monitoring air and water quality to mitigate pollution.
Public Transit Data		Promoting sustainable mobility.
Land Use Data		Balancing residential, commercial, and green spaces
Traffic Data		Enhancing road safety measures and accident analysis.
Public Health Data		Monitoring disease outbreaks
Public Health Data		Healthcare resource allocation.